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Noun-Noun Compound Comprehension As Self-Organization: The Representation And Processing Dynamics Of Noun-Noun Compounds

Pyeong Whan Cho

University of Connecticut - Storrs, pyeongwhan.cho@gmail.com

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Pyeong Whan Cho, Ph.D.

University of Connecticut, 2014

ABSTRACT

By *noun-noun compound*, we mean any combination of two nouns that native speakers of a language can understand. Native speakers can easily generate and understand novel, transparent compounds (e.g., mountain magazine), suggesting compositional processing. Relation-based theories of compound meaning (e.g., Levi, 1978) provide an explanation for this apparent productivity by assuming a set of semantic/thematic relations (e.g., ABOUT) that can bind two component nouns. Inspired by relation-based theories, we propose a self-organizing network model according to which (1) the meaning of a noun-noun compound $M\ H$ (e.g., mountain magazine) corresponds to a tree-like constituent structure whose daughter nodes represent constituent meanings and whose mother node represents a relation R such as $[_R\ M\ H]$, (2) each of the mother node and the daughter nodes is represented as a vector in a similarity space (in which similar relations are placed close together) that consists of multiple units (each of which is not necessarily interpretable) associated with activation levels, (3) connection strengths between units are assumed to be learned from linguistic experience, and (4) a particular structure (e.g., $[_{ABOUT}\ mountain\ magazine]$) is

realized from the interactive activation between the two groups of constituent units via the relational units. The model integrates prior efforts to model processing difficulty (Gagné & Shoben, 1997) and relational similarity (Devereux & Costello, 2006) to provide a comprehensive understanding of compound representation and processing dynamics. Furthermore, the model is applied to opaque compounds (e.g., seahorse) that have idiosyncratic meanings by assuming that they are represented in the same space as transparent compounds. We describe a free card sorting study that suggests that the relation space is a similarity space and hierarchically organized. In Experiment 1, we demonstrate that two kinds of interpretation revision phenomena, known from the sentence processing literature—garden path and local coherence effects—both occur in compound processing, suggesting an interactive constraint-satisfaction process. In Experiment 2, we observed positive priming between two transparent compounds that instantiate similar relations. In Experiment 3, we observed negative priming between an opaque and a transparent compound (and vice versa) regardless of relational similarity. Results in Experiment 2 and 3 together suggest that processing difficulty is not simply correlated with distance in similarity space: processing dynamics on the space must be considered. We report two simulation studies to explain experimental data and discuss why complex dynamics is observed in the relation similarity space. We contrast our model with symbolic treatments of the relation between regular and exceptional morphology (Pinker, 1999) and other similarity space models (Devereux & Costello, 2006), arguing that the critical distinguishing property of the dynamical models is the inclusion of feedback dynamics.

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Pyeong Whan Cho

M.A., Seoul National University, South Korea, 2002

B.A., Seoul National University, South Korea, 2000

A Dissertation

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Pyeong Whan Cho

2014

APPROVAL PAGE

Doctor of Philosophy Dissertation

**Noun-Noun Compound Comprehension As
Self-Organization: The Representation And
Processing Dynamics Of Noun-Noun
Compounds**

Presented by

Pyeong Whan Cho, B.A., M.A.

Major Advisor

Whitney Tabor

Associate Advisor

Jay Rueckl

Associate Advisor

James S. Magnuson

Associate Advisor

William Snyder

University of Connecticut

2014

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Contents

Ch. 1.	Introduction	1
1.1	Why study noun-noun compounds?	2
1.2	Background	4
1.3	Noun-noun compound comprehension as self-organization	9
1.3.1	Activation dynamics	11
1.3.2	The notion of a self-organizing treelet	13
1.3.3	The model's properties	15
1.4	Research hypotheses	16
1.4.1	Self-organization underlies online compound comprehension.	16
1.4.2	Relations are represented in a continuous vector space, separate from the representation space of concepts.	17
1.4.3	The continuous relation space is involved in the representations of both transparent and opaque compounds.	17
1.5	Overview	18
Ch. 2.	Dynamic self-organized semantics: Garden path and local coherence effects in online noun-noun compound comprehension	19
2.1	Introduction	19
2.2	Experiment 1	23
2.2.1	Methods	23
2.2.2	Results	26
2.2.3	Discussion	29
2.3	Simulation 1	34
2.3.1	Training corpus	35
2.3.2	Activation dynamics	36
2.3.3	Training	37

2.3.4	Result	38
2.3.5	Discussion	41
Ch. 3.	The structure of the relation space	43
3.1	Introduction	43
3.2	Free card sorting	44
3.2.1	Method	47
3.2.2	Results	49
3.2.3	Discussion	58
3.3	Experiment 2	59
3.3.1	Methods	60
3.3.2	Results	64
3.3.3	Discussion	69
Ch. 4.	A single mechanism view of noun-noun compound processing	72
4.1	Introduction	72
4.2	Experiment 3	75
4.2.1	Methods	75
4.2.2	Results	78
4.2.3	Discussion	82
4.3	Simulation 2	84
4.3.1	A corpus	85
4.3.2	Architecture	88
4.3.3	Activation dynamics	93
4.3.4	Results	94
4.3.5	Discussion	98
Ch. 5.	General discussion	100
5.1	Summary	100
5.2	Implications	103
5.3	Future directions	106
5.3.1	Representation and processing dynamics of noun-noun-noun compounds	106
5.3.2	Structure of the relation space	108
5.3.3	Learning neural network models	109
5.4	Conclusion	111
Ch. A.	Materials used in Experiment 1	112
Ch. B.	Materials used in Experiment 2	114

Ch. C. Materials used in Experiment 3	121
Ch. D. Materials used in a free card sorting task	127
Ch. E. The instruction used in a free card sorting task	132
Ch. F. The instruction used in a pairwise relational similarity rating task	135
References	137

Chapter 1

Introduction

In this study, we investigate the representation and processing dynamics of combinations of two nouns (e.g., “mountain magazine”) that seem to be productive and require compositional processing. The study of this minimal construction provides a chance to enhance our understanding of compositional processing due to its rich semantics and its apparently simple syntax. A way of treating rich semantics is to represent a meaning as a vector in a high dimensional continuous vector space. In our study, we argue that just the study of spatial configuration is not enough to model the processing data.

In this chapter, first we review the prior studies and make an argument that what we lack is an understanding of processing dynamics. We propose a computational model of compound comprehension that represents a structure in a similarity vector space and has feedback dynamics on the representation space.

1.1 Why study noun-noun compounds?

By *noun-noun compound*¹, we mean any combination of nouns that native speakers of a language can understand. Noun-noun compounds are roughly divided into two types, transparent and opaque compounds. A compound (e.g., “mountain squirrel”) is *transparent* or purely compositional if its meaning is systematically predictable from two component nouns’ literal meanings. A compound (e.g., “seahorse”) is *opaque* if it is not purely compositional. This study is about how transparent and opaque noun-noun compounds are represented in our mental system and processed in online language comprehension.²

Noun-noun compounds are particularly interesting for the following reasons. First, although noun-noun compounding is not universal across languages (Snyder, 2010), once a language allows noun-noun compounding, it seems to be recursive and productive. For example, native speakers of English can easily understand a transparent compound like “mountain squirrel” although they may not have heard it before. A traditional way to explain the apparent productivity is to presume a set of symbolic rules which can take constituent nouns as input and output a meaning. However, it is hard to specify the rules underlying the semantic patterns of all possible compounds without losing semantic details (Downing, 1977). An alternative to a rule system will be discussed.

Second, not all compounds are cleanly compositional. There exist a lot of opaque compounds that clearly have constituents with meanings related to the whole, but for which the meaning of the whole is not systematically predictable from the meanings of the parts, revealing that compounds are “structures at the crossroads between words and sentences reflecting both the properties of linguistic representation in the mind and grammatical pro-

¹To save space, we will often use a general term *compounds* to refer to *noun-noun compounds*.

²In fact, transparent and opaque compounds seem to lie on a continuum of compositionality (Reddy, McCarthy, & Manandhar, 2011) but we will make a categorical distinction in this study by choosing examples that are clustered into two groups and well separated on the continuum.

cessing” (Libben, 2006, p. 3). For example, consider “seahorse.” We easily perceive its constituents “sea” and “horse” but the compound has an idiosyncratic meaning that should be distinguished from its compositional meaning, something like “a horse that lives in a sea.” We need a theory that explains both transparent and opaque compounds. According to the *words-and-rules* theory (Pinker, 1991, 1997, 1999; Pinker & Ullman, 2002b), roots, idioms, irregulars, and some regulars are stored in and retrieved from a mental lexicon but phrases, sentences and any regular forms are computed by a rule system. It naturally follows that transparent compounds are computed by rules while opaque compounds are retrieved from the lexicon. On the basis of our results in Experiments 2 and 3, we will argue that the words-and-rules theory fails to predict the pattern of priming among transparent compounds and interference between transparent and opaque compounds which we observe. The study of compound comprehension provides a chance to reevaluate the proposals about the nature of rules (McClelland & Patterson, 2002a, 2002b; Pinker & Ullman, 2002a, 2002b; Tabor, 2009; Tabor, Cho, & Dankowicz, 2013; Tabor, Cho, & Szkudlarek, 2013). Spatial encoding of compound meanings (e.g., Devereux & Costello, 2006) provides a way to treat both transparent and opaque compounds in a single mechanism but we will argue in Chapter 4 that space alone is not enough because processing difficulty associated with a state change in the space depends not just on the distance between two states but also on the rate of change and/or the structure of the path of the state change.

Third, a good model of language comprehension should be able to explain processing difficulty associated with a wide variety of constituent structures. However, online comprehension of noun-noun compounds has not been extensively addressed in the psycholinguistics literature maybe because its syntax looks too simple to be interesting while its semantics looks too rich to study systematically in a psycholinguistic experiment (Gagné & Shoben, 1997, is a notable exception). We argue that if we think of compound meaning

as a constituent structure, such dual aspects of compounds provide us a chance to study complex processing dynamics involved in compound comprehension in particular and in incremental structure building in general. In this study, we propose a model that combines spatial encoding of such structure with a dynamical process to build the structure and report three experiments supporting the model.

1.2 Background

Noun-noun compounds as well as other types of compounds (e.g., verb-noun compounds like “whetstone”) have been extensively studied in linguistics (for review, see Libben, 2006; Lieber & Stekauer, 2009). A general claim can be made as follows: a novel noun-noun compound MH means “an H which is in relation R to M”(see Allen, 1978; Booij, 2009; Downing, 1977; Dowty, 1979; Jackendoff, 2010; Levi, 1978; Ryder, 1994; Snyder, 2010; Warren, 1978). H is a Head noun because it determines the compound’s syntactic and semantic properties. M is a Modifier noun because it modifies the head noun’s meaning. For example, a mountain magazine is a magazine which is ABOUT mountains (R = H-ABOUT-M) and a girl baker is a baker who IS-A girl (R = H-BE-M). From this point of view, noun-noun compound comprehension can be thought of as finding an appropriate relation R. The debate is about the nature of the space of relations.

Some researchers have argued that a small finite number of relations can capture a large portion of the semantic patterns of noun-noun compounds (e.g., Levi, 1978). Other researchers have argued that there are an infinite number of relations used in noun-noun compounds and it is not helpful to classify compounds into relation classes because doing so will gloss over important semantic details (e.g., Downing, 1977). Still other re-

searchers argue that there are many templates (Ryder, 1994) or constructions (Booij, 2009) across different abstraction levels which are reliably associated with specific relations. For example, according to Ryder (1994), a template “location-M + H” (e.g., *field mouse*, *mountain laurel*) is reliably interpreted as a “H that is located at/in M.” Templates can be more specific as in “weapon-M + human-H” (e.g., *gunman*, *axman*) which is interpreted as a “H who uses M usually as a professional killer or hunter”; or “tool-M + human-H” (e.g., *drillman*, *spademan*) which is interpreted as a “H who works using M”; or “product-M + human-H” (e.g., *mailman*, *basket woman*) which is interpreted as a H who “makes/sells/delivers/transport/processes M as a profession.”

Noun-noun compound comprehension is also important in natural language processing. Researchers in the field view compound comprehension as a classification problem requiring classification of noun-noun compounds into certain relation classes. For example, Lauer (1995b) proposed a probabilistic model that computes a probability distribution of relations given a compound.³ Wermter (1989) and Rosario and Hearst (2001) used feed-forward neural networks to classify compounds into relation categories. Girju, Moldovan, Tatu, and Antohe (2005) tested a few supervised learning models (including a support vector machine) to classify compounds into one of 35 semantic relations.

Cognitive psychologists have used novel compounds to understand *conceptual combination*. Conceptual combination refers to the process of combining simpler concepts to get more complex concepts or its product (for review, see Murphy, 2004). A major approach to conceptual combination is the schema modification (or concept specialization) theory (Murphy, 1988, 1990; Smith, Osherson, Rips, & Keane, 1988). On this approach, it is presumed that concepts are represented as “schemata which are structured lists of slots

³Actually, he suggested a list of eight prepositions (*of*, *for*, *in*, *about*, *with*, *from*, *on*, *at*) which can be used to paraphrase noun-noun compounds. See Lauer (1995b) for more details.

and fillers” (Murphy, 1988). For example, a schema for APPLE has slots for color, size, taste, etc. Those slots are filled with typical values (e.g., red for color). Then, conceptual combination (e.g., GREEN APPLE) is a process that modifies a concept (e.g., APPLE) by selecting some slots (e.g., color) and changing their values (e.g., from typical red to green). Now consider a novel noun-noun compound, “apartment dog.” According to the schema modification theory, this expression is understood by setting the value of the habitat slot from a typical value HOUSE to APARTMENT. This idea resembles the *Variable R Condition* (Allen, 1978); the meaning of the modifier noun fills a feature slot of the head noun that can be appropriately filled by the modifier.

Wisniewski and Love (1998) (also Wisniewski, 1997) proposed a dual process theory according to which two different processes, *property mapping* and *relation linking*, race in noun-noun compound comprehension. For example, consider “robin hawk.” The property mapping process maps some salient features (e.g., “has a red breast”) of the modifier noun to the head noun which results in a meaning, “a hawk with a red breast.” Simultaneously, the relation linking process tries to find a plausible relation between two component concepts (e.g., a PREY-PREDATOR relation) which results in another meaning, “a hawk that preys on robins.” Wisniewski and Love (1998) argue that it is more likely for the property mapping process to win when two component concepts are similar. We argue that the property mapping interpretation can be explained by a relation H-RESEMBLES-M (see also Gagné, 2000; Warren, 1978). While the relation-based approach predicts the competition between property-mapping and relation-linking interpretations, the dual process theory as a race model does not predict any competition. Until we observe evidence preferring one to the other, we prefer a more parsimonious relation-based approach.

Another major approach to conceptual combination is a relation-based theory where noun-noun compound comprehension is viewed as instantiating a relation that can integrate

two component concepts. Inspired by Levi (1978), Gagné and Shoben (1997) proposed a psychological model of online compound comprehension, the Competition-Among-Relations-In-Nominals (CARIN) model. According to the CARIN model, a small number of relations compete with each other to be chosen in conceptual combination; a relation more frequently used with a modifier noun is more likely to be chosen. Then, the chosen relation is evaluated in the context of a head noun. If the relation cannot go with the head noun, then another relation needs to be checked. This failure will introduce a delay in processing. Gagné and Shoben (1997) argued that the relation preference of the modifier noun influenced the processing difficulty of a compound while that of the head noun did not.

The psychological reality of the relation representation has been supported by relation priming studies. Gagné (2001) argued that processing a novel, transparent compound (e.g., “oil moisturizer”) instantiating a certain relation (e.g., H-USES-M) can facilitate processing another novel, transparent compound (e.g., “oil treatment”) instantiating the same relation (also see, Estes, 2003; Estes & Jones, 2006; Raffray, Pickering, & Branigan, 2007). Gagné and Spalding (2009) replicated the relation priming effect using lexicalized compounds. Spalding and Gagné (2011) argued that the comprehension of a lexicalized compound instantiating a relation was slower after processing another lexicalized compound instantiating a different relation but not faster after processing another lexicalized compound instantiating the same relation. We point out that prior studies have reported only positive priming between two compounds; we will report negative priming in Experiment 3.

Maguire, Maguire, and Cater (2010) (see also, Maguire, Wisniewski, & Storms, 2010) proposed two refinements of the CARIN model: (a) statistical information like relation instantiation frequency should be modeled not at the level of individual nouns but at the level of semantic classes (see also Warren, 1978); and (b) processing difficulty should

be modeled in terms of the interaction between modifier and head nouns. For example, although “chocolate” prefers the H-MADE-OF-M relation, “chocolate taste” instantiating the M-HAS-H relation can be easy to process because many combinations of the type [SUBSTANCE-ATTRIBUTE] are typically associated with the M-HAS-H relation.

An important elaboration of relation-based theories was proposed by Devereux and Costello (2006). Devereux and Costello (2006) proposed an exemplar model of compound meaning where a compound is represented as a vector in a high-dimensional continuous vector space. It is assumed that experienced compounds are stored as exemplars in the relation space. Then, the meaning of a novel compound is computed as the average of all exemplars each of which is weighted depending on conceptual similarity between constituent nouns. Using a relation selection task in which noun-noun compounds (e.g., “dog bed”) were presented with their interpretations (e.g., “a bed where a dog sleeps”) and then participants were asked to select any of 18 relations that could be an appropriate paraphrase for the interpretation, Devereux and Costello (2005) showed that participants were likely to select more than one relation and some relations were correlated with each other, suggesting that the relations intersect in the sense that sometimes many relations are valid for a single compound meaning.

Based on this literature review, we make the following arguments. First, a transparent compound MH means a “H that is in relation R to M.” Second, the compound meaning can be treated as a constituent structure, $[_R \text{ M H}]$, whose mother node represents a relation. From this perspective, compound comprehension requires building the constituent structure responding to the input of component nouns. Third, the structures (or compound meanings) are represented in a continuous vector space (Devereux & Costello, 2006) where similar structures (or relations) are placed close together. Unlike other relation-based approaches assuming a small number of relations, this framework can represent all transpar-

ent compounds’ meanings without losing semantic details and explain perceived similarity between relations used in two different compounds. Because it is a similarity space, the hierarchical organization of relations in the abstraction level is expected (Ryder, 1994). Third, opaque compounds are represented in the same format as transparent compounds in the same structure space. Fourth, the overall association pattern between constituent nouns and relations plays an important role in processing dynamics (Gagné & Shoben, 1997). Fifth, the relationship among compound relations introduces complex processing dynamics: processing a transparent compound instantiating a relation facilitates processing another transparent compound instantiating a similar relation (say, *positive priming*, [Gagné, 2001]); processing an opaque compound instantiating a relation suppresses processing another opaque compound instantiating a different relation (Spalding & Gagné, 2011); processing a transparent compound instantiating a relation suppresses processing an opaque compound instantiating a similar relation and vice versa (say, *negative priming*) which will be reported in Experiment 3.

1.3 Noun-noun compound comprehension as self-organization

We propose the self-organizing treelet model of noun-noun compound comprehension which can be implemented as a recurrent neural network with distributed representations of relations and constituent concepts. In this section, we will provide an overview of the model architecture and processing; then, in Sections 2.3 and 4.3 we will provide detailed descriptions of each of two simulations.

The architecture of the model is presented in Figure 1.3.1. The core of the model consists of three groups of units: y^M , encoding the modifier semantics, y^H , encoding the

head semantics, and y^R , encoding the relations.

Feeding in to the modifier encoding units is a group of word form units which encode the first word of a noun-noun compound; feeding in to the head encoding units is a group of word form units which encode the second word of a noun-noun compound. The word form units have indexical bit (or one-hot) encodings; only one unit has a value of 1 and every other unit has a value of 0.

Processing begins by turning on the word forms for the modifier and head in succession (Simulation 1) or together (Simulation 2). After one or more indexical word form unit are turned on, the model settles in the fashion of interactive activation networks (see Equations 1.3.1, 1.3.3, and 2.3.5 given below in Section 1.3.1 [p. 11]). It generally approaches a fixed point—a point where none of the unit activations are changing anymore. When the model is near a fixed point, the units on the relation layer can generally be interpreted

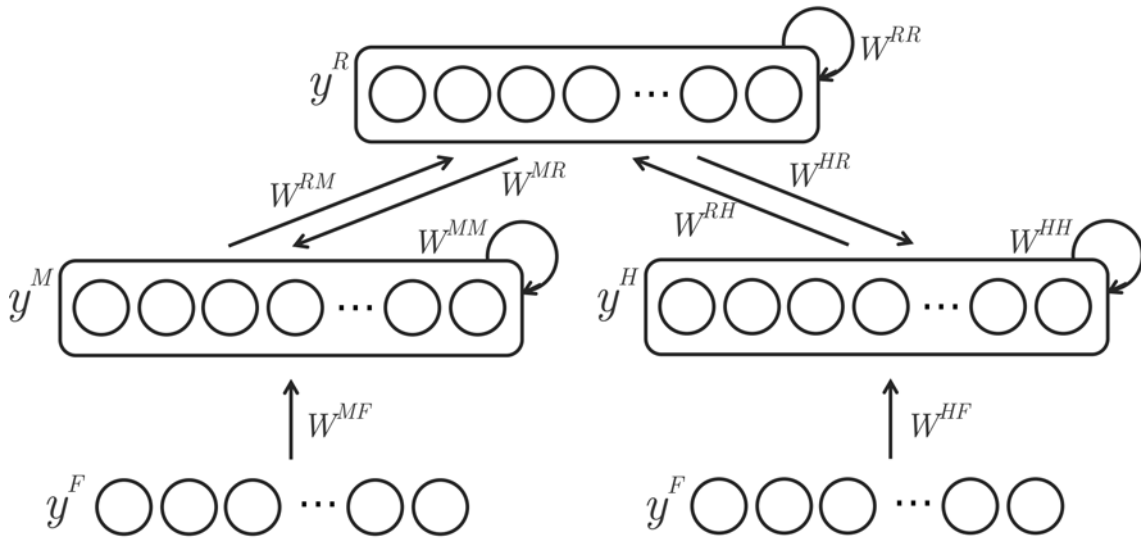


FIGURE 1.3.1: The architecture of the self-organizing treelet model. y^X is the activation state vector for group X and W^{XY} is a weight matrix of connections from group Y to group X. R = relation units, M = modifier word meaning units, H = head word meaning units, F = word form units. $W^{MM} = W^{HH}$ and $W^{MF} = W^{HF}$.

as specifying a particular relation; thus it is possible to find out what relation the model has chosen as an interpretation of the word form or forms presented to it. The number of processing steps required to get within a very small distance of a fixed point is taken as processing time; in this way, the model can be used to simulate reaction times in a self-paced reading experiment.

1.3.1 Activation dynamics

Let y be a concatenation of three vectors (r , m , h) that represents a specific relation, a modifier noun's meaning, and a head noun's meaning, respectively (see Figure 1.3.1). Let R , M , H , and F be a set of indices to the units representing a relation, a modifier noun meaning, a head noun meaning, and a word form. The change in the net input to the i -th unit, dx_i/dt , is computed by Equation (1.3.1).

$$\frac{dx_i}{dt} = \sum_j y_j w_{ij} + b_i + ext_i \quad (1.3.1)$$

where b_i is a bias, ext_i is an external word input, and w_{ij} is a weight from the j -th unit to the i -th unit. The unit's output activation (or state) is computed from the net input by a sigmoid function f :

$$y_i = f(x_i) = \frac{1}{1 + e^{-x_i}} \quad (1.3.2)$$

Because $\frac{df(x)}{dx} = f(x)(1 - f(x))$, by a chain rule, the state change of the unit is described in Equation 1.3.3 (Kukona, Cho, Magnuson, & Tabor, 2014; Tabor, Cho, & Dankowicz, 2013):

$$\frac{dy_i}{dt} = y_i(1 - y_i) \frac{dx_i}{dt} \quad (1.3.3)$$

In the actual simulation, the Euler integration with a time constant dt_X was used to approximate continuous state change as follows:

$$y_i^X(t+1) = y_i^X(t) + dt \cdot y_i^X(1 - y_i^X)x_i^X \quad (1.3.4)$$

Let w_{ij}^{XY} be a weight from the j -th unit ($j \in Y$) to the i -th unit ($i \in X$). Because two groups of units representing the modifier and head noun meaning are not directly connected to each other, $w^{MH} = w^{HM} = 0$. We assume that a word meaning is represented in the same way in two groups of units representing the modifier and head nouns. Thus, $w^{MM} = w^{HH}$ and $w^{MF} = w^{HF}$. Because relation units do not receive any external input, $ext_i = 0$ ($i \in R$). While a modifier noun is presented to the model, $ext_i = \sum_j y_j w_{ij}$ ($i \in M$ and $j \in F$). While a head noun is presented to the model, $ext_i = \sum_j y_j w_{ij}$ ($i \in H$ and $j \in F$). Otherwise, $ext_i = 0$. In this study, localist representation was used for word form representation such that for the i -th word input, $y_i = 1$ ($i \in F$) and $y_j = 0$ ($j \in F, j \neq i$).

In a simulation, two component nouns of a compound can be presented sequentially (Simulation 1) or simultaneously (Simulation 2). Given the word input (i.e., the word form vector using one-hot coding), the model updates its states in all three groups either until the relation state vector becomes very close to the target relation state vector or until a certain amount of time (which is a free parameter) passes.

The model receives word form inputs and activates a relation as well as modifier and head noun meanings. The backpropagation through time algorithm (Rumelhart, Hinton, & Williams, 1986) can be used to train the model to activate the target state t given word form inputs.

1.3.2 The notion of a self-organizing treelet

The relation units play a role of binding two constituent concepts in a unique way; the model can be viewed as a recurrently connected parallel distributed processing (PDP) model (e.g., McClelland & Rogers, 2003) of treelets whose mother node represents syntactic/semantic relations; for this reason, our model is called the Self-Organizing Treelet.⁴

We do not consider cases where treelets combine to form larger tree structures here, although this is possible and is a natural approach to complex compounds. In this sense, our model should be distinguished from SOPARSE (Tabor & Hutchins, 2004) that combines treelets to form large structures, although competition for fit with the bottom-up input gives rise to interference effects that slow processing in both models. Another difference is that SOPARSE treelets are stipulated in the architecture whereas treelets modeled by our model are emergent; the treelets arise out of interactions among activating relation units and conceptual units.

In Simulation 1 we explore a model that learns its weights; in Simulation 2 we hand-wire the weights in order to better understand the causes of the processing dynamics. The model can learn to activate a relation given a sequential or simultaneous input of two nouns. Unlike exemplar models (Devereux & Costello, 2006; Kruschke, 1992; Nosofsky, 1986; Pierrehumbert, 2001), knowledge about the experienced compounds (or exemplars) is stored in the configuration of connections among simple processing units and influences the model's response to novel compounds. The model can develop abstractions of particulars at many different levels (McClelland & Rogers, 2003; Tabor, Cho, & Dankowicz, 2013). The model can be thought of a parallel distributed processing version of a construction grammar account (Booij, 2009) or a cognitive grammar account (Ryder, 1994) of

⁴The model can be used to model other types of treelets like [NP Adj N] (e.g., “red apple,” “rural policeman,” or “difficult mountain”) or [NP Det N] (e.g., “the dog”).

noun-noun compounds in the sense that the model can implement schema at many different abstraction levels like ‘ $M_A H$ ’ meaning $[R_1 M_A H]$ (M_A indicates M is a noun of semantic class A) and ‘ $M_{A'} H$ ’ meaning $[R_2 M_{A'} H]$ ($M_{A'}$ indicates M is a noun of a subclass of A). This kind of model can handle apparently rule-governed, productive linguistic patterns (transparent compounds) as well as exceptional, idiosyncratic linguistic patterns (opaque compounds) (e.g., Elman, 1990; Plaut, McClelland, Seidenberg, & Patterson, 1996; Tabor, Cho, & Dankowicz, 2013; Tabor, Cho, & Szkudlarek, 2013).

Regarding processing dynamics, it is important to understand the notion of *self-organization*. In a self-organizing system (e.g., a flock of bird flying in a formation), components of the system are continuously influencing and influenced by other components and a macro-level structure emerges from the interaction. The proposed model is a self-organization model in the following sense. Each unit has a particular state. Responding to external word input, units are interacting with each other with continuous feedback dynamics and the collection of the states forms a pattern at a macro level, corresponding to a treelet. More specifically, the successive input of two nouns activates the conceptual (or lexical semantic) units and the relation units associated with the constituent nouns context-independently and the interaction among those units is stabilized at a particular activation pattern which corresponds to a particular treelet. As will be clear below, this self-organization model makes a new prediction about the processing difficulty of different types of compounds. For example, consider “paper magazine” which is most likely to mean a magazine MADE-OF paper. Because the target relation is preferred by the modifier noun, the CARIN model does not predict any processing difficulty. However, the self-organizing treelet model predicts processing difficulty in this case because the bottom-up support from the head noun units to the relation units will compete with the bottom-up support from the modifier noun units to the relation units.

1.3.3 The model's properties

The model has a single mental state space to represent compound relations as well as other syntactic/semantic relations and the space is a complete metric space (Barnsley, 1993). States are simply feature vectors with semantic/syntactic interpretations. Relational similarity is defined as a function of distance in the metric space. Similar relations are located close together. But an important aspect of our model is the model has rich dynamics, which are a set of continuous differential equations that map from state to state changes (the vector field). A word input specifies the dynamical parameters and changes dynamics and the topology as well. A succession of words results in a complex trajectory through the relation space. The system needs to get to an appropriate meaningful interpretation upon processing each word but different sequences of words make this happen more or less efficiently thus the model predicts variations in processing time corresponding to response times or reading times in psycholinguistic experiments. Processing time is explicitly modeled as convergence time; the time required to arrive at the target state.

A crucial insight is that greater distance of travel can result in longer processing time (corresponding to similarity effects) but slower speed or a more circuitous path can also result in longer processing time. Thus, dynamics play a crucial role in the processing time predictions. The interactivity (feedback) in such systems makes cause and effect potentially complex but we can analyze the systems to understand the principles of cause and effect in key cases of interest.

1.4 Research hypotheses

Based on the self-organizing treelet model of compounds, we propose three specific research hypotheses.

1.4.1 Self-organization underlies online compound comprehension.

A transparent noun-noun compound (e.g., “mountain magazine”) can be understood by instantiating a semantic relation (e.g., H-ABOUT-M) which can combine two component nouns (e.g., “mountain” and “magazine”). While Gagné and Shoben (1997) viewed compound comprehension as a sequential process of a selection of a candidate relation and then the evaluation of the appropriateness of the chosen relation, we argue that compound comprehension is a case of self-organization by which a constituent structure is constructed by co-activating the relation as well as two concepts associated with component nouns. Given that the constituent nouns are input sequentially, the hypothesis predicts both garden path and local coherence effects (for more details, see Experiment 1). The garden path effect refers to a phenomenon in which context creates a strong expectation which turns out to be wrong later so processing difficulty is observed when it becomes clear that the expectation is wrong. The local coherence effect refers to a phenomenon in which the bottom-up input of words create a locally coherent but globally incoherent interpretation which competes to the globally coherent interpretation.

1.4.2 Relations are represented in a continuous vector space, separate from the representation space of concepts.

The mental space for relation representation is a high dimensional continuous vector space. The space is a similarity space such that similar relations are located close to each other. The continuity of the relation space allows representing an infinite number of relations while capturing the apparent distinction among relation classes by the distribution of noun-noun compounds in the space. Because the self-organizing model has a separate representation space for relations, it predicts relation priming between two transparent compounds (Gagné, 2001, 2002) even when their component nouns are different. Furthermore, the model predicts that the amount of relation priming would be a function of relational similarity in cases where other factors are equal (Estes & Jones, 2006). Experiment 2 was designed to test this hypothesis.

1.4.3 The continuous relation space is involved in the representations of both transparent and opaque compounds.

The continuous relation space is used in the representations of both transparent and opaque compounds. Consider the words-and-rules approach, according to which opaque compounds are represented as wholes in the lexicon while unfamiliar transparent compounds are computed by rules. A challenge for this approach is that the compositionality of noun-noun compounds seems to be on a continuum rather than all-or-none (Reddy et al., 2011). A good theory of noun-noun compounds should be able to explain the continuum of compositionality between transparent and opaque compounds. The continuity motivates the hypothesis that the same continuous relation space is involved in both transparent and opaque compounds, which predicts relation priming between transparent and opaque compounds

in a bidirectional way. Experiment 3 was designed to test this prediction.

1.5 Overview

In Chapter 2, we test the first hypothesis by investigating if local coherence as well as garden-path effects are observed in online compound comprehension. We also ask whether if alternative models can explain the result pattern. In Chapter 3, regarding the second hypothesis, we propose a new method—a card sorting task—to study the structure of the relation space and test if (a) relation priming is observed in sentence comprehension and (b) the amount of priming is graded. In Chapter 4, we investigate if the priming between transparent and opaque compounds is observed. All those three experiments will reveal that symbolic models and vector space models with no feedback dynamics are not appropriate for understanding compound comprehension in particular, and language comprehension in general. In Chapter 5, we review and evaluate the self-organizing treelet model with experimental results. The implication of this study will be discussed in a broader context. Finally, we present the future direction of this study.

Chapter 2

Dynamic self-organized semantics: Garden path and local coherence effects in online noun-noun compound comprehension

2.1 Introduction

In this chapter, we investigate processing dynamics underlying online comprehension of novel noun-noun compounds in a minimal context. We argue that compound comprehension is possible by a self-organizing process that forms a constituent structure $[_R \text{ M H}]$. By taking this view, we can discuss compound processing in more general context of sentence processing.

In sentence processing literature, it is well known that people tend to prefer a particular interpretation in an ambiguous situation. This case is well demonstrated by a famous example, “the horse raced past the barn . . .,” in incremental processing. Although there are

two interpretations possible right after processing “barn” (see Figure 2.1.1), native speakers strongly prefer the first interpretation, although the interpretation might turn out to be incorrect, for example, as when a word “fell” follows the phrase. One theory of what happens mentally during the processing of such sentences holds that the mind is led to build an erroneous parse tree structure up through the word “barn”—it is led down a “garden path” and has to retrace its steps when “fell” occurs. Based on this conception, such sentences are called “garden path sentences.” According to rational models of sentence processing (Hale, 2001; Jurafsky, 1996; Levy, 2008), the garden path effect is evidence that human language processing is rational and optimal in the sense that it constructs the most likely structure given context and the current word input. The effect has been interpreted as evidence of context-dependent, top-down processing.

On the other hand, there are some cases in which native speakers do not seem to rely wholly on context. Consider a sentence “The coach smiled at the player tossed a frisbee by ...” Given the context “the coach smiled at,” the only possible interpretation of “the player ...” is as presented in the left side of Figure 2.1.2. However, in a self-paced reading experiment, human participants read the region “the tossed a frisbee by” more slowly (Tabor, Galantucci, & Richardson, 2004). According to Tabor et al. (2004), this is because people construct a locally coherent constituent structure (see the right of Figure 2.1.2) which conflicts with the globally coherent structure. The effect is called the *local coherence* effect

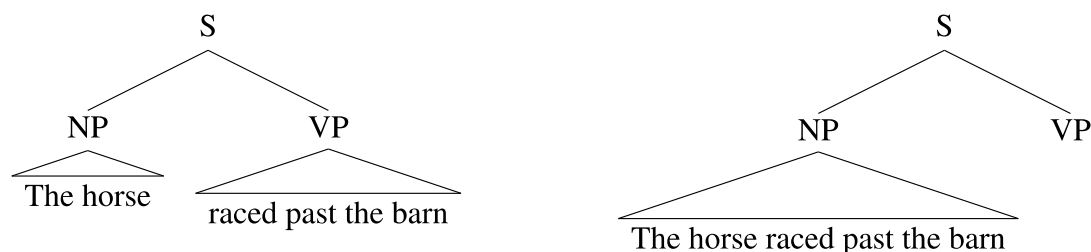


FIGURE 2.1.1: Two possible interpretations of “The horse raced past the barn ...”

and interpreted as evidence for context-independent, bottom-up processing.

There have been lively debates about the source of the local coherence effect. According to Tabor et al. (2004), a language processing system is a self-organizing system in which multiple elements associated with different constraints interact with each other to form a globally coherent structure. During this process, temporarily, a locally coherent structure can be constructed. But the fact that the garden path and local coherence effects have been studied using different linguistic constructions makes it hard to compare them directly.

There are long-known lexical autonomy effects. For example, an ambiguous word “bugs” seems to activate both its meanings even in a biasing context like “spiders, roaches, and other bugs” (Swinney, 1979). Kukona et al. (2014) argue that these cases are 1-word “local coherence” effects—they have bottom up interference from just one word. We argue that a similar situation can arise with the second word of a noun-noun compound.

Noun-noun compounds provide us a chance to investigate both effects in the same con-

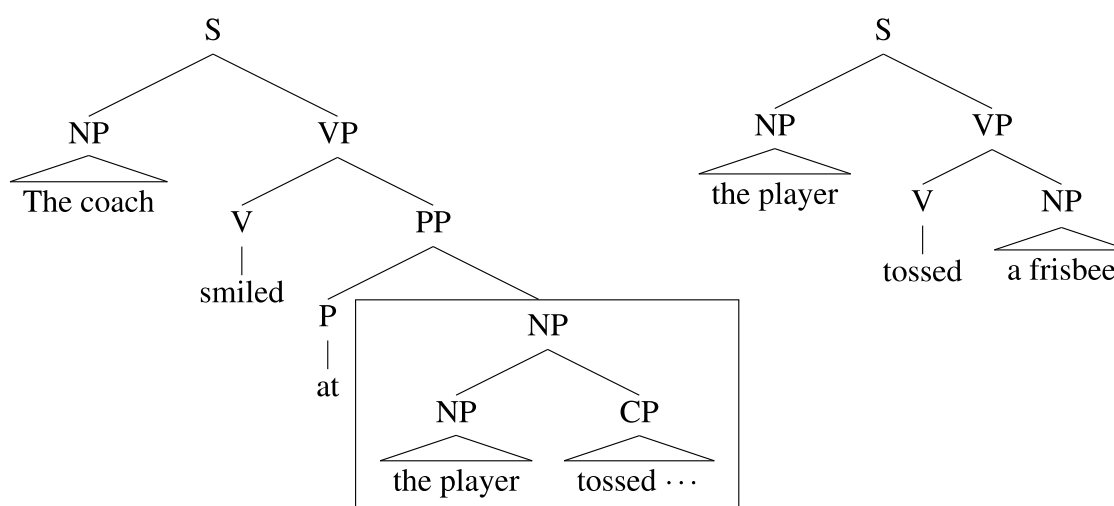


FIGURE 2.1.2: A globally coherent (i.e., correct) interpretation (left) and a locally coherent interpretation (right) of “the player tossed a frisbee ...”

struction. Remember that Gagné and Shoben (1997) argued that compound comprehension is slow if the modifier noun strongly prefers a non-target relation of a compound because the non-target relation is more likely to be chosen as a candidate relation which will turn out to be incorrect in the evaluation process with the head noun. This is thus a case of a garden path effect that occurs during the processing of a two-word compound. But Gagné and Shoben (1997) argued that compound comprehension is fast if the modifier strongly prefers the target relation regardless of whether the head noun prefers the same relation or not; in other words, according to them, there is no local coherence effect—indeed, they tested for local coherence effects but did not find them. Then, the CARIN model can be interpreted as a version of rational models. On the other hand, the self-organizing treelet model predicts both garden path and local coherence effects in compound comprehension.

Experiment 1 was designed (1) to replicate the effect of modifier-noun relation preference (Gagné & Shoben, 1997), supporting the current relation-based approach; and (2) to test for an effect of head-noun relation preference, in an effort to distinguish between the CARIN model and supporting the self-organizing treelet model. The effects can be viewed as garden path and local coherence effects, respectively. Finding both effects in the same construction type suggests that those effects are not qualitatively different. It will be argued that the notion of self-organization provides a unified account of both effects (see also, Kukona et al., 2014).

2.2 Experiment 1

2.2.1 Methods

Participants

Forty-two undergraduate students at the University of Connecticut participated for course credit. All participants were native speakers of English. Two participants were excluded from further analyses because they reported reading disability (N=1) or did not complete the experiment (N=1).

Materials

We constructed 15 triples of sensible noun-noun compounds that shared the same head noun (e.g., *math magazine*, *paper magazine*, *mountain magazine*) and 45 nonsense noun-noun combinations (e.g., *vegetable pains*) (see Appendix A). All nonsense combinations and many sensible noun-noun combinations were from Gagné and Shoben (1997). As in Gagné and Shoben (1997), sensible and nonsense combinations were presented in the following sentence frame: “[Name] [Verb] about the [Noun1] [Noun2] in the [Time].” (e.g., *Fred thought about the math magazine in the morning.*).

Sensible compounds were chosen such that they could be classified into one of three types based on the component nouns’ relation preferences. The context-independent relation preference of a noun as modifier (or head) was determined as follows. The twenty most frequent noun-noun compounds (e.g., *paper bag*, *paper towel*) which share a modifier (or a head) noun (e.g., *paper*) were sampled from the Corpus of Contemporary American English (COCA; Davies, 2008) and classified by the author into one of 15 thematic relations¹

¹The relations (examples) are H-CAUSES-M (flu virus), M-CAUSES-H (college headache), H-HAS-

used in Gagné and Shoben (1997). The most frequent relation (e.g., H-MADE-OF-M) in terms of token frequency was chosen as the relation that the noun (e.g., *paper*) as a modifier (or a head) noun prefers out of context. To get the relation preference of constituent nouns, Gagné and Shoben (1997) asked participants to create sensible combinations given a set of nouns. They classified the produced compounds into one of 14 relations and then constructed a relation frequency distribution for each noun as modifier once and as head noun once. In this study, we used a corpus because we believe this method approximates the unknown real relation preference distribution better (Maguire, Devereux, Costello, & Cater, 2007).

To minimize the effect of repeating the same head noun in three trials, 45 sensible and 45 nonsense combinations were separated into three blocks of 15 sensible and 15 nonsense combinations such that each block consisted of 5 compounds for each of three experimental conditions and no head noun occurred more than once within a block. The presentation order of 3 blocks was counterbalanced by using the Latin square design, resulting in three stimulus lists. In each block of each stimulus list, the trial presentation order was randomized.

Design

We used a single-factor within-subject design in which the relation preference of modifier and head nouns of compounds was manipulated across three levels (Baseline [BL], Local Coherence [LC], and Garden Path [GP]). In the baseline condition (e.g., *math magazine*), both modifier and head nouns preferred the same target relation (e.g., H-ABOUT-M). In

M (picture book), M-HAS-H (lemon peel), H-MAKES-M (milk cow), H-MADE-OF-M (chocolate bird), H-FOR-M (cooking toy), M-BE-H (dessert food), H-USES-M (gas antiques), H-ABOUT-M (mountain magazine), H-LOCATED-M (mountain cloud), H-USED-BY-M (servant language), M-LOCATED-H (murder town), H-DERIVED-FROM-M (oil money), H-DURING-M (winter cloud).

the local coherence condition (e.g., *paper magazine*), the modifier noun preferred the target relation (e.g., H-MADE-OF-M) but the head noun preferred a non-target relation (e.g., H-ABOUT-M). In this condition, the head noun preferred a locally coherent but globally incoherent interpretation (e.g., H-ABOUT-M) when context preferred a globally coherent and correct interpretation (e.g., H-MADE-OF-M). In the garden path condition (e.g., *mountain magazine*), the modifier noun preferred a non-target relation (e.g., H-LOCATED-AT-M) while the head noun preferred the target relation (e.g., H-ABOUT-M). As in garden path sentences, context (i.e., the modifier) creates a strong expectation for a wrong interpretation (e.g., H-LOCATED-AT-M) which needs to be revised when the head noun is encountered.

Procedure

Participants read sentences each of which contained one sensible or nonsense noun-noun combination and then judged if the combination made sense or not. Unlike Gagné and Shoben (1997), we used a non-cumulative, moving window, self-paced reading task (Just, Carpenter, & Woolley, 1982) to mimic sequential word input in spoken sentences. More specifically, participants pressed the space bar to begin each trial and read a sentence in a word-by-word fashion by pressing the space bar. When participants pressed the space bar after reading the last word, the screen was cleared and a phrase “Sensible?” appeared on the screen. Participants pressed “F” for yes or “J” for no response to make sensibility judgments. We used E-Prime software (Version 1.2, Psychology Software Tools, Inc., Pittsburgh, PA) to run the experiment. The experiment was approximately 15 minutes long.

2.2.2 Results

Individual mean accuracy in the sensibility judgment task was investigated. Two participants whose mean accuracy was equal to or lower than 0.7 were excluded from further analysis.² The acceptance rate (AR) of noun-noun combinations is presented in Appendix A. Three nonsense noun-noun combinations with $\text{AcceptanceRate} > 0.5$ were excluded from further analysis as well as 4 sensible noun-noun compounds with $\text{AcceptanceRate} < 0.5$. The 4 sensible noun-noun compounds with low AcceptanceRate and 12 other compounds that shared the same head noun with the 4 compounds were excluded from statistical analyses of the experimental materials.

Word reading times in self-paced reading were first log-transformed. Log word reading times greater than 2.5 SDs from the individual mean log reading time per word region were trimmed to 2.5 SDs from the mean; reading times lower than 50 ms were trimmed to 50 ms. Then, individual mean word log reading time was investigated. One participant was excluded from further analysis because the individual's mean log reading time was greater than 2.5 SDs from the average of individual mean log reading times. For counterbalancing, one more participant was excluded; we chose the first 12 participants who were assigned to List 3.³ The following analyses were based on 36 participants.

Sensibility judgment

The mean accuracy in the sensibility judgment task was .937 ($SD = .084$) in the baseline condition, .869 ($SD = .120$) in the local coherence condition, and .899 ($SD = .106$) in the garden path condition. A generalized linear mixed-effects model (Jaeger, 2008) with a logit

²The criterion of 0.7 was decided after investigating the distribution of individual mean accuracy in the task. The criterion was the same as what Gagné and Shoben (1997) chose in their Experiment 1.

³We got the same pattern in the analysis with all 38 participants.

link function was used to test if trial-level accuracy in sensibility judgment was a function of compound types (CompType: baseline, local coherence, and garden path). CompType was dummy coded with baseline as a reference level. By-subject and by-item random intercepts and their interactions with the fixed-effect term (CompType) were also considered.⁴ The accuracy in the baseline condition was significantly different from neither the accuracy in the local coherence condition ($b = -0.819$, $SE = 0.642$, $p > .201$) nor the accuracy in the garden path condition ($b = -0.561$, $SE = 0.647$, $p > .385$).

The mean sensibility judgment time was 471 ms (SD = 202 ms) in the baseline condition, 572 ms (SD = 233 ms) in the local coherence condition, and 606 ms (SD = 259 ms) in the garden path condition. A linear mixed-effects model (Baayen, Davidson, & Bates, 2008) was used to test if log-transformed trial-level response time was a function of compound types. Sensibility judgment was slower in the local coherence condition ($b = 0.142$, $SE = 0.065$, $p < .043$) and in the garden path condition ($b = 0.154$, $SE = 0.065$, $p < .029$) than in the baseline condition.

Self-paced reading

The mean word reading time (in msec) is presented in Figure 2.2.1. Word reading times were log-transformed to make the distribution of word RTs normal. Following Hofmeister (2011), the log-transformed reading times were analyzed in two steps. First, log word RTs were regressed on (a) the logarithm of trial numbers in the experiment (to take into account possible practice or fatigue effects), (b) the number of letters (WordLen) (to consider the word length effect), and (c) a factor distinguishing between experimental and filler stimuli.

⁴All analyses in this study were performed in *R* (R Core Team, 2013) using the *lme4* (Bates, Maechler, Bolker, & Walker, 2014) and *lmerTest* (Kuznetsova, Bruun Brockhoff, & Haubo Bojesen Christensen, 2014) packages.

Unlike Hofmeister (2011), we didn't include word position in each sentence because we do not agree with his argument that word reading times can be modeled by a cubic spline function.⁵

In the second step, the residual log reading time averaged across the head noun position plus two following words (i.e., “in the”) was analyzed using a linear mixed-effects model. More specifically, CompType as well as logarithm of compound frequency (in COCA) and log reading time of modifier noun were included as fixed-effect terms. We included the latter two variables in order to control (a) processing difficulty associated with different modifier nouns (spillover) and (b) the effect of compound frequency because we used different modifiers across three CompType conditions. CompType was dummy coded with baseline as a reference level. By-subject and by-item random intercepts and their interactions with CompType were considered as well.

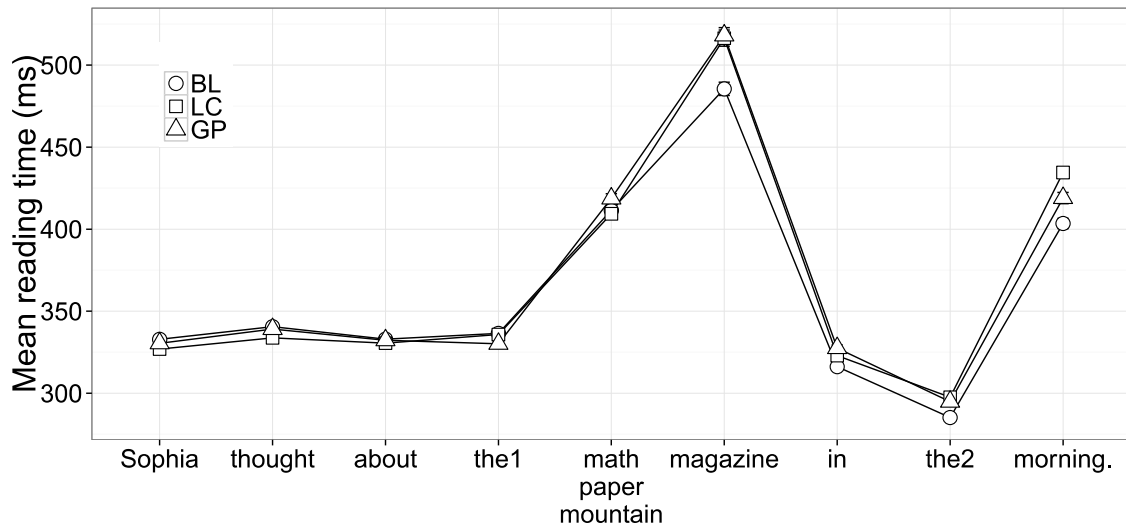


FIGURE 2.2.1: Mean reading time (ms) per word region

⁵The functional form will depend on the sentence structure. For examples, our data reported in Experiment 2 cannot be modeled by a cubic spline.

TABLE 2.2.1: Summary of fixed-effects (N = 1071, Deviance = -715.08). LC = local coherence, GP = garden path, M = Modifier, NNfreq = COCA compound token frequency.

	<i>b</i>	<i>SE</i>	<i>df</i>	<i>t</i>	<i>p</i>
Intercept	-0.2902	0.1130	808.9	-2.569	.0104
CompType = LC	0.0475	0.0199	16.8	2.386	.0291
CompType = GP	0.0572	0.0213	17.9	2.691	.0150
logRT(M)	0.0517	0.0184	839.2	2.806	.0051
log(NNfreq+1)	0.0002	0.0074	25.4	0.026	.9792

The coefficient estimates of fixed-effect terms and their *p*-values are presented in Table 2.2.1. The degrees of freedom were estimated by the Satterthwaite’s approximation for degrees of freedom.⁶ Participants read the same head noun significantly more slowly in the local coherence condition and in the garden path condition than in the baseline condition when processing difficulty associated with different modifiers was statistically controlled, supporting the self-organizing treelet model’s prediction of both (bottom-up, context-independent) local coherence and (top-down, context-dependent) garden path effects. The coefficient of the log reading time of modifier nouns was also statistically significant, suggesting a spill-over effect from modifier to head nouns. But the logarithm of COCA compound frequency was not significant.

2.2.3 Discussion

The CARIN model does not predict the local coherence effect. However, the analysis of residual log reading times across the region of interest suggests both garden path and local coherence effects in online compound comprehension, supporting the self-organizing treelet model of compounds. Recall that Gagné and Shoben (1997) argued the garden path

⁶The `lmerTest` package was used to compute the *p*-values with the Satterthwaite’s approximation of degrees of freedom. The model comparisons with likelihood ratio tests revealed the same pattern.

effect was observed but the local coherence effect was not observed.

The difference in the result patterns may stem from the way the two studies selected the relation preference of nouns. Gagné and Shoben (1997) sampled 100 combinations from Levi (1978) and combined 91 head nouns and 91 modifier nouns to construct 3,239 sensible combinations. Then, the authors classified them into 15 relation classes. The relation frequency distribution was investigated for each modifier and head noun. For example, $\text{Freq}(\text{N}) = \{\text{Freq}(\text{R}_1), \text{Freq}(\text{R}_2), \dots\}$ where $\text{Freq}(\text{R}_1) \geq \text{Freq}(\text{R}_2) \geq \text{Freq}(\text{R}_3) \geq \dots$. The most frequent k relations were treated as high-frequency relations for the noun if $\frac{\sum_{n=1}^k \text{Freq}(\text{R}_n)}{\sum_{n=1}^{15} \text{Freq}(\text{R}_n)} \geq .6$. The other relations were treated as low-frequency relations for the noun. The scheme considers multiple high-frequency relations for a constituent noun rather than choosing the most frequent relation. More importantly, they considered a very limited sample of nouns from Levi (1978). However, Maguire et al. (2007) argued that the best method to estimate the distribution is to use a large-scale corpus. Maguire et al. (2007) used the British National Corpus (BNC) World Edition to randomly sample 100 compounds for each of the modifier and head nouns used in Gagné and Shoben (1997). They argued that the relation frequency estimated from Gagné and Shoben (1997) was different from the estimation of the information by using a corpus. As in Maguire et al. (2007), we used a corpus (COCA) to sample 20 most frequent compounds to decide the relation preference for each noun.

Probabilistic models

In this section, we show that two representative probabilistic models of sentence processing (incremental structure building), the surprisal model (Levy, 2008) and the entropy reduction hypothesis (Hale, 2006), cannot explain our result.

Let us assume that a noun-noun compound is understood by instantiating a semantic relation from a set of discrete semantic relations, $R = \{r_1, r_2, \dots, r_N\}$. Let P_M be a probability distribution after processing a modifier noun M ; $P_M(i) = P(r_i|M)$.⁷ Let P_H be a probability distribution after processing both a modifier noun and a head noun H ; $P_H(i) = P(r_i|M, H)$.

The surprisal model (Levy, 2008) predicts that the reading time of H , RT_H , is a function of surprisal, $-\log(P(H|M))$,⁸ which is equivalent to Kullback-Leibler divergence of P_H from P_M .⁹ The K-L divergence, $D_{KL}(P_H||P_M)$, is as follows:

$$D_{KL}(P_H||P_M) = \sum_{i=1}^N \log \left(\frac{P_H(i)}{P_M(i)} \right) P_H(i)$$

The entropy reduction hypothesis (Hale, 2006) predicts that RT_H is a function of entropy reduction by H which is as follows:

$$ER(H) = \max(0, -\sum P_M \log(P_M) + \sum P_H \log(P_H))$$

For simplicity, let us assume that there are only two relations. Let r_1 be the target relation of a noun-noun compound MH . Because there are only two relations, $P_M(2) = 1 - P_M(1)$ and $P_H(2) = 1 - P_H(1)$. Thus, each number of $P_M(1)$ and $P_H(1)$ uniquely specifies a probability distribution. Figure 2.2.2 presents D_{KL} (left) and ER (right) (in gray scale) as

⁷For the simplicity, we assume a minimal context such that $P(r_i|M) = P(r_i|context, prefix, M)$ where *context* is a pragmatic context or a discourse context and *prefix* is a sequence of words before the modifier noun.

⁸In a minimal context, $P(H|context, prefix, M) = P(H|M)$.

⁹The surprisal model and the entropy reduction model consider a probability distribution across a set of *complete structures*, not a set of partial structures like $[_r M H]$. When a context-free grammar is assumed as a generative mechanism, however, the probability of a complete structure is a product of probabilities assigned to multiple partial structures. Note that sentential context was minimal and not likely to prefer a particular relation interpretation in Experiment 1. We can assume that probabilities assigned to partial structures other than noun-noun compound structures are same across the baseline, local coherence, and garden path conditions. Thus, we compare the probability distributions across the partial structures of noun-noun compounds instantiating different relations in those three conditions.

a function of $P_M(1)$ and $P_H(1)$. Given a certain value of $P_H(1)$, while D_{KL} is a monotonic function of $P_M(1)$, ER is a monotonic function of $|P_M(1) - 0.5|$.

Now consider three different types of compounds used in the experiment. Given that r_1 is the target relation of a compound MH, $P_H(1)$ must be very high, say 0.9, and must be equal to or greater than $P_M(1)$ in all three conditions. In the baseline condition, both $P_M(1)$ and $P_H(1)$ are high. In the local coherence condition, as in the baseline condition, both $P_M(1)$ and $P_H(1)$ are high. For discussion, let $P_M(1)$ be 0.7. In the compounds used in the garden path condition, $P_M(1)$ is low, say 0.3, but $P_H(1)$ is high. Here we chose specific values of $P_M(1)$ and $P_H(1)$ for three conditions but the logic presented below holds regardless of specific values.

Figure 2.2.2i suggests that D_{KL} predicts the garden path effect; when $P_H(1)$ is high (e.g., 0.9), D_{KL} is higher in the top left region (e.g., $P_M(1) = 0.3$) than in the top right

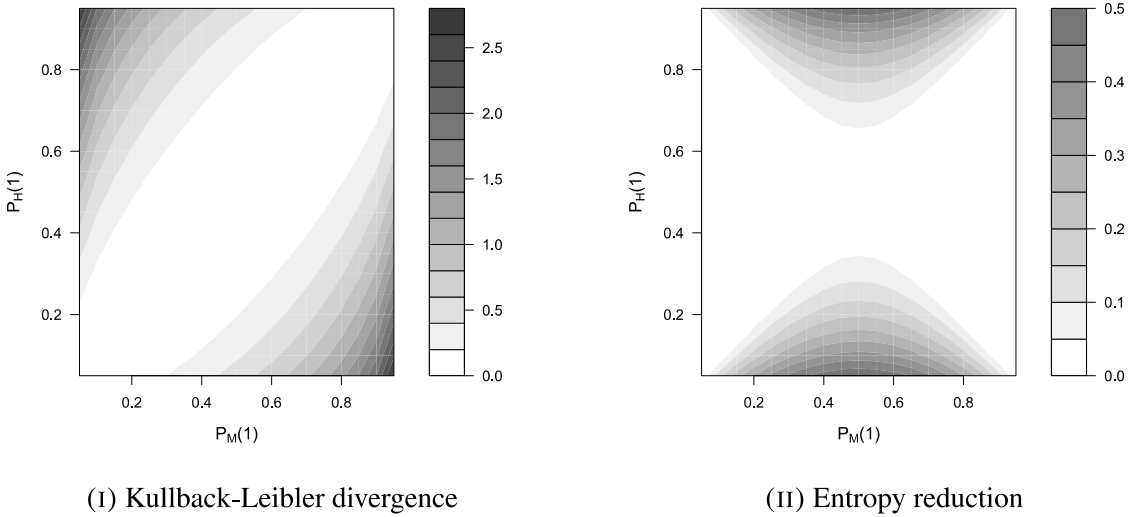


FIGURE 2.2.2: Kullback-Leibler divergence (left) and entropy reduction (right) as a function of $P_M(1)$ and $P_H(1)$. The reading time of a head noun is slower with the distribution pairs corresponding to darker regions than with the distribution pairs corresponding to lighter regions.

region (e.g., $P_M(1) = 0.7$). However, the measure does not predict the local coherence effect because the local coherence cases cannot be distinguished from the baseline cases in terms of $P_M(1)$ and $P_H(1)$.

Figure 2.2.2ii suggests that the entropy reduction hypothesis does not predict the local coherence effect and sometimes the garden path effect as well. Regarding the garden path effect, consider the following cases. When $P_M(1) = 0.3$ and $P_H(1) = 0.9$, $ER(H)$ is high. A high value of the measure indicated by a dark color predicts processing difficulty associated with the head noun H. However, the entropy reduction measure has the same value when $P_M(1) = 0.7$ and $P_H(1) = 0.9$ that corresponds to baseline and local coherence conditions. In other words, $ER(H)$ is not sensitive to the relation preference of the modifier noun in the same fashion as in empirical data. The entropy reduction hypothesis does not explain the local coherence effect because $P_M(1)$ and $P_H(1)$ are comparable between baseline and local coherence conditions.

The lesson is clear. If we consider two distributions P_M and P_H as two different mental states, we can say that the Kullback-Leibler divergence and the entropy reduction quantifies how different two mental states are. Then, we can think of a generalized state space model that predicts processing difficulty as a function of (something like) the distance between those two mental states. Because the mental states before and after processing a head noun are comparable between baseline and local coherence conditions, any state space model without feedback dynamics cannot explain the local coherence effect.

2.3 Simulation 1

In this section, we report a simulation which gives us an insight about why garden path and local coherence effects are observed in online compound comprehension. For our purpose, it is enough to use a simple version of the self-organizing treelet model which uses localist representations of relations. We made the model as simple as possible to make it easier to understand. The network architecture is presented in Figure 2.3.1. The model consists of 2 relation units, 20 modifier noun meaning units, 20 head noun meaning units, and 20 word form units.

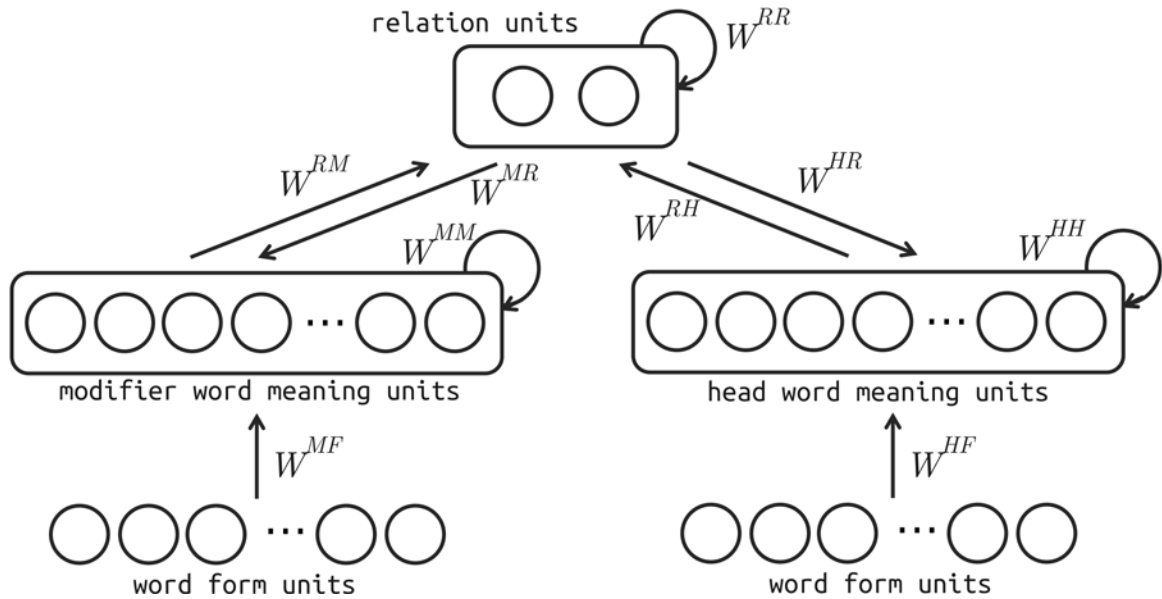


FIGURE 2.3.1: Architecture of the model used in Simulation 1. In the first phase of training, the network was trained to activate the target word meaning given a word form; in this phase, W^{MM} and W^{MF} were updated. After the first phase, we made another copy of the word form to word meaning network to get $W^{HH}(=W^{MM})$ and $W^{HF}(=W^{MF})$ and connected two groups (M and H) of units with a new group (R) of units. In the second phase, the network was trained to activate the target relation and the modifier and head word meanings given a sequential input of a compound; only W^{MR} , W^{RM} , W^{HR} , W^{RH} , and W^{RR} were updated while the other weights were frozen. For details, see text.

2.3.1 Training corpus

The training corpus is presented in Table 2.3.1. It consists of 16 compounds each of which instantiates one of two relations R1 and R2; R1 is represented as (1, 0) and R2 is represented as (0, 1).¹⁰ Twenty nouns (W1, W2, ..., W20) were used as a modifier noun or a head noun in these compounds. Each noun meaning was represented as a 20 dimensional vector, $(a_1, a_2, a_3, \dots, a_{20})$, whose element a_i was randomly sampled from a uniform distribution on [0, 1]. These relation and word meaning vectors were used as target state vectors when training the model.

The corpus was created such that W2 and W3 as modifier prefer R1 to R2 while W4 as modifier prefers R2 to R1. W1 as head prefers R1 to R2. For example, in the training corpus, W2 was used as a modifier noun in three compounds C1, C4, and C5 two of which instantiate R1. Thus, the conditional probability of a compound instantiating R1 given that a modifier noun is W2 is 2/3. In this sense, W2 prefers R1 to R2. In a similar way, W1 (used in compounds C1, C2, and C3) prefers R1 to R2. The first three compounds were used as test compounds for baseline, local coherence, and garden path conditions in Experiment 1. The first compound has R1 as its target relation which was preferred by both modifier and head nouns. The second compound has R2 (e.g., MADE-OF) as its target relation. Its modifier noun (e.g., paper) prefers the target relation but its head noun (e.g., magazine) prefers a non-target relation (e.g., ABOUT). The third compound has R1 (e.g., ABOUT) as its target relation. Its modifier noun (e.g., mountain) prefers a non-target relation (e.g., IN) while its head noun (e.g., magazine) prefers the target relation.

A compound's meaning is represented as a triple of three vectors that represents rela-

¹⁰In principle, the model can represent an infinite number of relations by using distributed representations of relations across many relation units; there are an infinite number of vectors each in a high-dimensional continuous vector space each of which corresponds to a unique relation.

TABLE 2.3.1: Training corpus (16 compounds) for Simulation 1

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16
Relation	R1	R2	R1	R1	R2	R2	R1	R2	R2	R1	R1	R2	R2	R2	R1	R1
Modifier	W2	W3	W4	W2	W2	W3	W3	W4	W4	W12	W13	W14	W16	W17	W18	W19
Head	W1	W1	W1	W5	W6	W7	W8	W9	W10	W11	W11	W11	W15	W15	W15	W20

tion, modifier, and head, respectively.

2.3.2 Activation dynamics

Let y_i^X be the activation state of the i -th unit of group X ($X \in \{R, M, H, F\}$). Let x_i^X be the net input to the i -th unit. The changes in the net inputs x_i^R , x_i^M , and x_i^H are computed as follows:

$$\frac{dx_i^R}{dt} = \sum_{j \in R} y_j^R w_{ij}^{RR} + \sum_{j \in M} y_j^M w_{ij}^{RM} + \sum_{j \in H} y_j^H w_{ij}^{RH} + b_i^R \quad (2.3.1)$$

$$\frac{dx_i^M}{dt} = \sum_{j \in M} y_j^M w_{ij}^{MM} + \sum_{j \in F} y_j^{F(M)} w_{ij}^{MF} + b_i^M \quad (2.3.2)$$

$$\frac{dx_i^H}{dt} = \sum_{j \in H} y_j^H w_{ij}^{HH} + \sum_{j \in F} y_j^{F(H)} w_{ij}^{HF} + b_i^H \quad (2.3.3)$$

$y_i^{F(M)} = 1$ only when the i -th word was presented as modifier and $y^{F(M)} = 0$ otherwise. Similarly, $y_i^{F(H)} = 1$ only when the i -th word was presented as head and $y^{F(H)} = 0$ otherwise.

The rate of change in y_i^X is as follows:

$$\frac{dy_i^X}{dt} = y_i^X (1 - y_i^X) \frac{dx_i^X}{dt} \quad (2.3.4)$$

In the actual simulation, the Euler integration with a time constant dt_X was used to

approximate continuous state change as follows:

$$y_i^X(t+1) = y_i^X(t) + dt \cdot y_i^X(1 - y_i^X)x_i^X \quad (2.3.5)$$

where $dt = 0.1$.

To avoid problems with roundoff, we set the minimal and maximal activation values to 0.01 and 0.09, respectively.

2.3.3 Training

Training was done in two phases. In the first phase, a part of the model (a group of word form units, a group of word meaning units, and the connections from word form to word meaning units) was trained to activate the target word meaning state given a word form input. In this phase, the model changed the weights from the word form units to the word meaning units and the recurrent weights from the word meaning units to the word meaning units (see W^{MF} and W^{MM} in Figure 2.3.1). At the beginning of a trial, one word form (one hot-bit vector) was clamped to the word meaning units. Then, the word meaning units update their states during 20 time steps under the influence of the clamped word form input. Then, the word form input was removed but the network was allowed to update its state for an additional 20 steps. We used this scheme to encourage the network to keep the current state for an amount of time even after the input word was removed. The weights were updated three times per trial, once after 20 time steps of each word input and once after 20 time steps of pause. The weights were updated with a delta rule:

$$\Delta w_{ji} = \alpha(t_j - y_j)y_i \quad (2.3.6)$$

where t_j is the j -th unit's target state and y_i and y_j are the i -th and j -th units' activation states right before the weights were updated. The learning rate α was set to 0.01.

In the second phase, the model was trained to activate the target relation, modifier, and head states given a compound input. For this purpose, we combined two copies of the pretrained word-form to word-meaning networks to the relation subnetwork to get a whole self-organizing treelet model: one with W^{MM} and W^{MF} , and one with W^{HH} and W^{HF} where $W^{MM} = W^{HH}$ and $W^{MF} = W^{HF}$. In the second phase, the weights from word form units to word meaning units and from word meaning units to word meaning units were frozen. Only the weights between modifier word meaning and relation, the weights between head word meaning and relation, and the recurrent weights from relation to relation units were updated (see W^{RM} , W^{MR} , W^{RH} , W^{HR} , and W^{RR} in Figure 2.3.1). During one trial, a word form unit corresponding to the modifier noun (connected to the modifier word meaning units) was turned on for 20 times steps. The network was allowed to update its modifier, head, and relation states during that time. Then, the word form unit was turned off and another word form unit corresponding to the head noun (which was connected to the head word meaning units) was turned on for 30 time steps. The network continued updating its states. Then, the word form unit was turned off but the network was allowed to update its states for an additional 30 time steps. Again the delta rule (Eq. 2.3.6) was used to update the weights in this state.

2.3.4 Result

We ran 20 simulations with different initial random weights. Then, we tested if those networks correctly activated the target state. The test was run in the following way. First, a compound's modifier noun was presented for the first 20 time steps. And the compound's

head noun was presented to the model until (1) the time steps exceed the maximal time steps (= 80) or (2) the relation state change is smaller than a certain criterion (= .00001) during 10 time steps, suggesting that the relation state is relatively stable. The response time was the number of time steps that the network needs to satisfy one of the above conditions. To compute accuracy, we compared the end state to each of the target states associated with different nouns and different relations. Only when the end modifier state was the closest to the current modifier noun state, the end head state was the closest to the current head noun state, and the end relation state was the closest to the target relation state, was the network considered to correctly process the compounds. Figure 2.3.2 presents 20 networks' response accuracy and times for the first three compounds that corresponded to Baseline, Local Coherence, and Garden Path conditions in Experiment 1. The overall pattern resembles the human participants' behavior patterns; in Experiment 1, we observed neither garden path nor local coherence effects in human sensibility judgment accuracy (see Section 2.2.2 [p. 26]) but we observed both garden path and local coherence effects in self-paced reading time measures (see Table 2.2.1 in Section 2.2.2 [p. 29]).

To understand why the response times were slower in both local coherence and garden path conditions than in baseline conditions, we investigated the relation state trajectories from a sample network. Figure 2.3.4 presents the relation state change responding to three compounds. The blue trajectory corresponds to the baseline compound (C1), the red trajectory corresponds to the local coherence compound (C2), and the green trajectory corresponds to the garden path compound (C3). Each open circle corresponds to a relation state at a particular time step, giving the information of how fast the relation state change was during a certain period. W1 and W2 indicates when the first noun (W1, modifier) and the second noun (W2, head) was presented to the network.

Consider the blue trajectory first. From the beginning, the relation state moved to the

target relation state which was (1,0). This is because the compound's modifier noun preferred the target relation. When the compound's head noun was presented (see W2 on the figure), the rate of relation state change was boosted, portrayed by larger gaps between open circles. This is because the model received bottom-up support from the head noun which was consistent to the bottom-up support from the modifier noun. Thus, the relation state could quickly move toward the target relation state.

Now consider the green trajectory corresponding to Garden Path condition. At the beginning, the relation state moved toward the non-target relation (1,0) because the compound's modifier noun preferred the non-target relation. The model traces a path that goes first in one direction, then makes an about-face, and goes in another direction. In this way it implements a mechanism very similar to that of the theory that inspired the name, "garden path." But when the head noun was presented, the network uses the bottom-up support from the head noun to overcome misleading bottom-up support from the modifier noun to

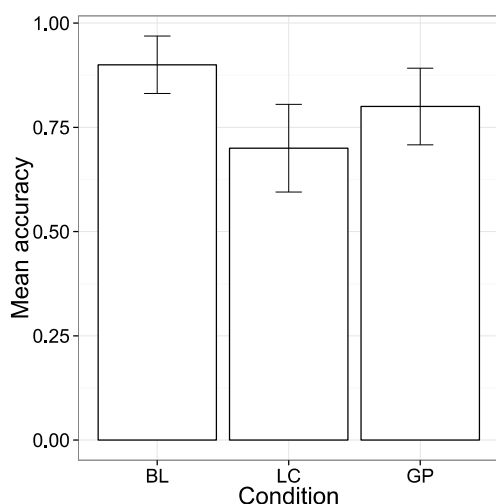


FIGURE 2.3.2: Mean accuracy of 20 networks for the compounds C1 (BL = Baseline), C2 (LC = Local Coherence), and C3 (GP = Garden Path)

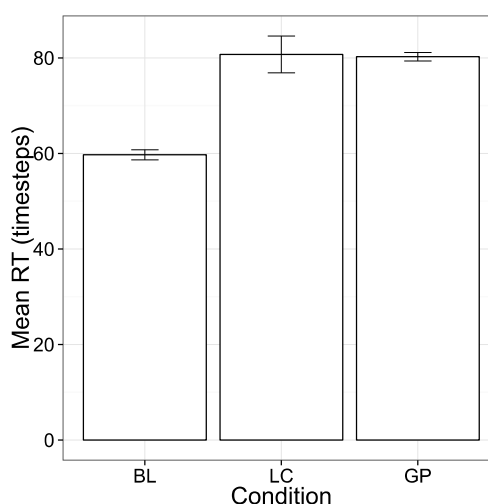


FIGURE 2.3.3: Mean response times of 20 networks for the compounds C1 (BL = Baseline), C2 (LC = Local Coherence), and C3 (GP = Garden Path)

change its direction of relation state change. The relation state with the new, and stronger support from the head noun moved toward the correct target relation state. In this case, the response time was delayed because initially the system was misled.

Finally, consider the red trajectory corresponding to Local Coherence condition.¹¹ From the beginning, the relation state moved toward the target relation state, similar to the BL trajectory. But when the head noun was input, the relation state change was slowed down, indicated by dense open circles on the trajectory. This is because from this point, the relation units received a contradictory force from the head noun. At the time when the head noun was given to the model, the R1 unit was more highly activated based on the modifier noun units' support and was suppressing its competitor R2 unit. When the head noun of the LC compound was presented to the model, the R2 unit received bottom-up support from the head noun units that made the R2 unit resist the inhibitory force from the R1 unit a little longer. Thus, temporarily, the rate of state change was slowed. But the contradictory information from the head noun was not enough to overcome the support from the modifier noun. Thus, the model was able to arrive at the target relation state anyway.

Figure 2.3.5 presents the relations state change during timesteps 45-50, showing the response time difference.

2.3.5 Discussion

The model unites garden path and local coherence effects in one mechanism by treating structural desiderata as soft constraints that compete over time until a stable resolution occurs. This allows the system to be temporarily led in one direction which is then reversed

¹¹ Actually, in this condition, the target relation is R2. To make trajectory comparisons easier, the trajectory was redrawn by exchanging two relation units' values. In the text, I treated as if the compound's target relation is R1.

(garden path case) and it allows the local information of the head noun to compete with the preference of the modifier noun temporarily without, in the end, overcoming it (local coherence effects).

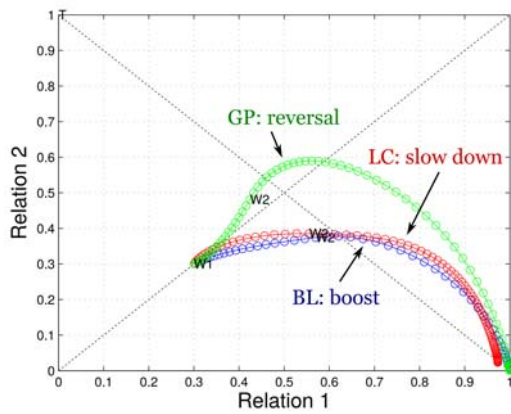


FIGURE 2.3.4: Sample trajectories of relation state change responding to the baseline (BL), local coherence (LC), and garden path (GP) compounds (C1, C2, C3)

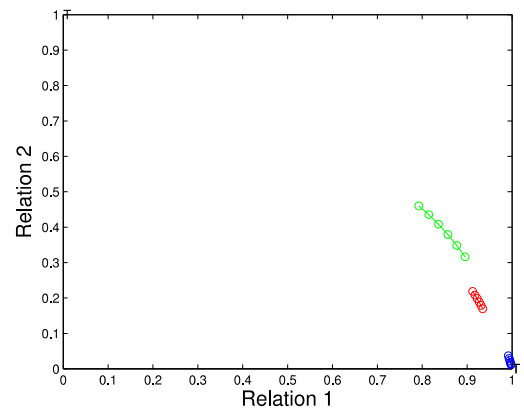


FIGURE 2.3.5: A subset (timesteps 45-50) of sample trajectories of relation state change responding to the baseline (BL), local coherence (LC), and garden path (GP) compounds (C1, C2, C3)

Chapter 3

The structure of the relation space

3.1 Introduction

In this chapter, we investigate the structure of the relation space that is assumed by the self-organizing treelet model and other relation-based theories of compounds. In the first part, we propose a new method (free card sorting) to investigate the organization of the relation space and describe data (collected from a small number of participants; $N = 7$)¹ which was used when analyzing Experiment 2 and preparing for Experiment 3.

¹We collected data from only seven participants because it was difficult to recruit people for the very long initial version and the participant pool ran out when we were trying to do replication with a shorter version. Tullis and Wood (2004) ran a simulation study of real sorting data of 46 cards ($N = 168$) to investigate the optimal number of participants for card sorting. They computed a correlation coefficient between the similarity matrix (see Section 3.2.2) constructed from a random sample of participants ($N = k$) and the full similarity matrix constructed from all participants ($N = 168$) for a certain value of k . The higher the correlation coefficient is, the more similar two sets of sorting data are. The correlation coefficient increased quickly as a function of k and when $k = 15$, the average correlation coefficient was around 0.90. When $k = 30$, the measure was about 0.95. Based on the result, the authors recommended recruiting 20-30 participants. But it is worth noting that the measures were 0.75, 0.82 when $k = 5, 8$, respectively, with greater standard deviations. The expected average correlation coefficients will depend on (1) how many cards and (2) what kind of materials participants sorted. We argue that our data set ($N = 7$) can provide information enough for our exploration purpose.

The main hypothesis is that the relation space is a continuous metric space (Hypothesis 2). It implies that relational similarity between two compounds is graded on a continuum. To test the hypothesis, we propose two more specific hypotheses about the organization of the relation space. Hypothesis 2A (Clustering): compound relations form a small number of groups each of which is well separated from other groups. Hypothesis 2B (Hierarchical Organization): the relation space is hierarchically organized such that each group of compound relations consists of multiple subgroups. If both are true, it suggests that the relation space is graded because a compound relation grouped into one subgroup of a group, Group 1, would be closer to another compound relation grouped into another subgroup of Group 1 than a third compound relation grouped into a different relation group, say Group 2.

Based on Hypothesis 2, we propose a hypothesis on processing dynamics (Hypothesis 2C: Graded Structural Parallelism Effect) that the amount of structural priming between two constructions (or relation priming between two compounds) is a function of relational similarity (c.f., Estes & Jones, 2006). The hypothesis is consistent with a spatial encoding model with only simple processing dynamics (e.g., Devereux & Costello, 2006). In the second part, we report an experiment that was designed to test Hypothesis 2C.

3.2 Free card sorting

In this section, we propose a new method to study the organization of the relation space and investigate if the method is useful for testing specific research hypotheses on the relation space structure.

Many researchers (e.g., Girju et al., 2005; Lauer, 1995b; Levi, 1978; Ó Séaghdha, 2008; Ryder, 1994; Warren, 1978) have proposed a finite number of relation classes into which

noun-noun compounds can be classified. The relation classes were mainly decided by researchers' expert knowledge or their perception of relational similarity. The resulting list of relations can be well elaborated but the decision can also be arbitrary. Actually, there is no consensus on how many and what relations are involved in noun-noun compound comprehension. Let us call this approach a top-down, discrete category account of the relation space.

On the other hand, several researchers have approached the question in a bottom-up way, using a continuous space. For example, Nakov (2008) recruited human participants through the Amazon Mechanical Turk Web Service and asked them to paraphrase noun-noun compounds in a structured way. For example, given a form “‘neck vein’ is a vein that the neck,” participants were asked to “substitute the dots with one or more verbs optionally followed by a preposition” (Nakov, 2008, p. 108). He defined a compound relation as a response frequency distribution across a set of reported verbs. In other words, a relation is represented as a vector in a high-dimensional vector space each of whose dimensions corresponds to a particular meaning (captured by a particular verb). Relational similarity was defined as the cosine similarity of two such vectors. The method has not been applied to a study of the relation space structure.

Devereux and Costello (2005) first generated a list of relations in a theory-driven way and then reconstructed the relation space in a bottom-up way as follows. In their experiment, participants performed a relation selection task in which they were given a noun-noun compound with its interpretation (to avoid possible ambiguity) and chose any number of relations among the predefined set of relations that they believed could paraphrase the compound. For each participant, an $N \times P$ matrix was constructed such that each row corresponds to a compound and each column corresponds to a relation (e.g., H-FOR-M) in the predetermined set. If a participant selected the i -th, j -th relations for a k -th compound,

then the i -th and j -th elements of the k -th row will be set to 1 and the other elements of the row will be set to 0. By aggregating the matrices across participants and normalizing it, the method represents a compound meaning as a vector in the P -dimensional space. In Devereux and Costello (2006), they applied Principal Component Analysis (which is a dimensional reduction technique) to their 19-dimensional data and discovered 6 dimensions that they argued correspond to M-GENERATES-H, H-CONTAINS-M, M-IS-H, H-USED-BY-M, H-GENERATES-M, and H-ON-THE-OCCASION-OF-M. It is not clear how the pattern supports their argument for the continuous relation space, although their cluster analysis of each relation class reported in Devereux and Costello (2005) suggests continuity of the relation space.

The relation selection task has both advantages and disadvantages compared to our sorting task. A clear advantage is that the task is easy to run such that participants can perform the task with a large number of compounds. Also a participant's response to a compound does not influence much the participant's response to another compound because participants are given a fixed reference set of relations that they can use. However, we point out that the task has a crucial problem which might give us an incorrect picture of the relation space. The problem is that the predetermined set of relations typically contained two relations that are different in the argument order (e.g., M-HAS-H and H-HAS-M; H-CAUSES-M and M-CAUSES-H). Given the task situation, it is highly unlikely that a participant selects both M-HAS-H and H-HAS-M relations for a compound. Thus, the two relations would be placed far away from each other in the relation space. However, participants might feel that the two relations are rather similar (Jackendoff, 2010).

We propose a purely data-driven method to investigate the relation space. The method is free card sorting. For example, Chaffin and Herrmann (1984) used the free card sorting task to investigate the structure of the semantic relation space. In their task, participants were

given 31 cards each of which contained 5 pairs of words that represented the same relation (e.g., smile-laugh, hungry-starving, brutal-unkind, dirty-soiled, torment-annoy holding the “dimensional similarity” relation). Participants sorted those cards into any number of piles such that the same or similar relations could be grouped together. We applied the same method to more limited cases, the relations instantiated in noun-noun compounds.

Card sorting has several advantages. The task is easy to implement; less susceptible to demand characteristics; and relatively easy to use a large number of stimuli (Whaley & Longoria, 2009). Many participants feel performing the task is not boring and even fun if the number of items is not too large.

3.2.1 Method

Participant

Seven University of Connecticut students voluntarily participated in a free card sorting task. Five of them were undergraduate students and the other two (including the author) were graduate students studying psycholinguistics. One of them (the author) was a non-native speaker of English.

Materials

A set of 630—384 transparent and 246 opaque—noun-noun compounds was prepared for the free card sorting task (see Appendix D). Transparent compounds were sampled from Levi (1978), Gagné and Shoben (1997), the COCA, or constructed by the author. Opaque compounds were sampled from Levi (1978) or selected from an online version of the Merriam-Webster dictionary (<http://www.merriam-webster.com>) by the author. We tried

to include a wide range of relations when selecting compounds. Although the compound set might not be representative of the unknown true distribution of relation frequency in English, it is not likely that similarity rating is highly influenced by a specific sample once the sample contains a wide range of relations.

Every compound was hand-written on a 3 x 5 inch index card. Multiple decks of 630 cards were prepared.

Procedure

An instruction (see Appendix E) was given to the participants who were gathered in the same place. They were informed with several examples that noun-noun compounds can be understood by instantiating a relation that binds component nouns. Then, they were informed that the task was to sort the cards into any number of groups (at least more than one group) such that each group contained similar noun-noun compounds in terms of the relations. The notion of relational similarity was introduced with a few examples and it was emphasized that (a) two compounds can be relationally similar even when their component nouns look different, and (b) two compounds can be relationally different even when their component nouns look similar. Once participants understood the task goal, they were given a more detailed instruction about a 2-stage card sorting task. The instruction was uploaded online to make it accessible to participants so that they could refer to it at any time.

Participant performed a 2-stage card sorting task individually when they were free and where they wanted. At the first stage, participants performed a typical free card sorting task. Based on relational similarity, they could sort cards into any number of groups. At the second stage, participants performed the same task again with each group of cards and separated each group of cards into multiple subgroups only when they found subgrouping.

Once they finished the task, they returned the experimenter a set of card piles which were separated by card guides with group labels. Participants reported that it took about 3 hours to sort 630 cards.

3.2.2 Results

Among 630 cards, on average, 2.3 cards (SD = 2.1) were missing and 17.4 cards (SD = 15.9) were classified into a “nonsense” group. The average number of groups and its standard deviation was 16.6 (SD = 5.4) at the first stage, and 31.4 (SD = 7.4) at the second stage. In the following analyses, we used the card sorting data at the first stage.²

We used a simple method to convert card sorting data to relational similarity scores. First, an individual k 's card sorting was coded as a 630 x 630 square matrix S_k ($k = 1, 2, \dots, 7$) in which $S_k(i, j) = 1$ if the i -th compound and the j -th compound were grouped together and $S_k(i, j) = 0$ otherwise ($i, j = 1, 2, \dots, 630$). Those square matrices were averaged across seven participants to get a similarity matrix S . Thus, $S(i, j)$ indicates a proportion of participants who grouped the i -th compound and the j -th compound together, which was considered as relational similarity between the two compounds. For the further analyses, we constructed another 384 x 384 matrix S_T by considering relational similarity between transparent compounds. We report the analysis of S_T (hereafter referred to as S) below.³

Figure 3.2.1 visualizes the similarity matrix S in a heat map format. Each column or

²We collected the second-level sorting data for the purpose of collecting more fine-grained similarity measures. We do not report the analysis of the second-level sorting data because it would be more unreliable than the first-level sorting data if the number of sorters is small. Given the small number of participants ($N = 7$), we do not report the analysis of this second-level sorting data. However, relational similarity measures computed from two levels of sorting data were highly correlated, $r = .903, p < .000001$.

³We focus on transparent compounds to make the distribution of canonical relations clear. The overall pattern was similar when all compounds were considered.

each row in the figure corresponds to a particular compound. Each cell corresponds to a pair of compounds. The color represents pairwise relational similarity—the relative number of participants who grouped the pair of compounds together; darker colors indicate higher relational similarity. To reveal the overall structure, columns and rows were re-

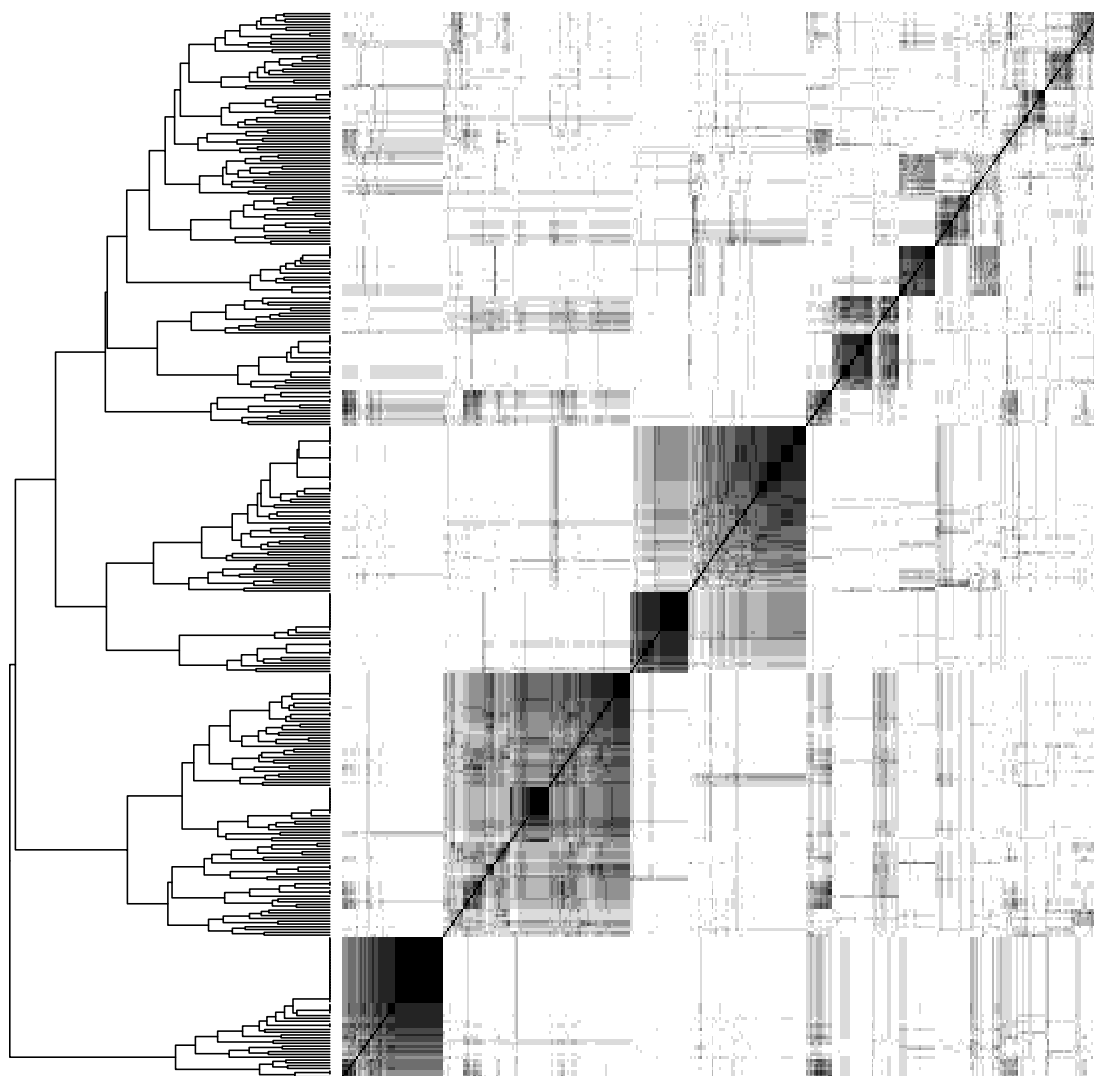


FIGURE 3.2.1: Heatmap of the similarity matrix S . Darker colors indicate higher relational similarity.

ordered by applying hierarchical clustering. There are several blocks of dark cells each of which corresponds to a relation class (e.g., H-IN-M), supporting Hypothesis 2A (Clustering). Moreover, some classes seem to have multiple subgroups. For example, consider two smaller and darker blocks inside a large block around the center of the figure, corresponding to two subclasses of a relation class (e.g., H-IN:LOCATION-M and H-IN:TIME-M). Relational similarity is lower between two subgroups, indicated by light gray colors, than inside each of two subgroups; however, relational similarity between two subgroups is higher than relation similarity between two different groups. This pattern supports Hypothesis 2B (Hierarchical organization).

Multidimensional scaling (Borg & Groenen, 2005; Croft & Poole, 2008; Shepard, 1980) was applied to the similarity scores to reconstruct the relation space. Multidimensional scaling is “a method that represents measurements of similarity (or dissimilarity) among pairs of objects as distances between points of a low-dimensional multidimensional space” (Borg & Groenen, 2005). This technique allows us to locate compounds in an n -dimensional vector space. First, a dissimilarity matrix D was constructed such that $D = 1 - S$ because $S(i, j)$ should be in the interval of $[0, 1]$. Given that perceived dissimilarity (or similarity) is not a simple linear function of distance (Shepard, 1987), nonmetric multidimensional scaling was applied.⁴ The appropriate number of dimensions was decided by finding an elbow point in a scree plot of stress against number of dimensions. *Stress* is a measure of

⁴In nonmetric multidimensional scaling, dissimilarity is treated as an ordered variable, not an interval variable. Distance is assumed to be any monotonic function of dissimilarity which is unknown. By the iterative process, the method tries to find the configuration of data points in which the ordered relationship between dissimilarity and estimated distance holds best. In this study, the `isoMDS` function in the `MASS` package (Venables & Ripley, 2002) was used for nonmetric multidimensional scaling. Assuming that dissimilarity between two different compounds must be greater than dissimilarity between two identical compounds, dissimilarity of 0 between two different compounds was replaced with a small value of 0.001.

goodness-of-fit and defined as follows:

$$Stress = \sqrt{\frac{\sum_{i,j} (d_{ij} - \hat{d}_{ij})^2}{\sum_{i,j} d_{ij}^2}} \quad (3.2.1)$$

where d_{ij} is the Euclidean distance between two points at the current configuration of data points and \hat{d}_{ij} is a number that is monotonic with $D(i, j)$ and minimize stress relative to d_{ij} (for details, see Borg & Groenen, 2005). Based on Figure 3.2.2, each novel compound was assigned to a 4-dimensional vector.

Clustering of compound relations

Recall Hypothesis 2A that relation classes are well separated in the relation class. If this is true, we expect that the vectors of compounds form a small number of groups in the space. To investigate if there is clear grouping of compounds, a k -means clustering was applied to

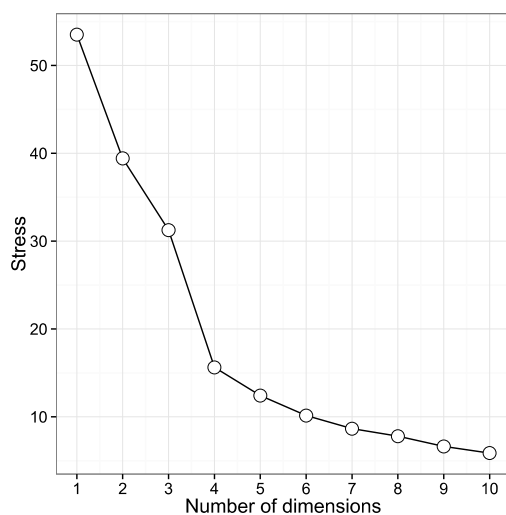


FIGURE 3.2.2: A scree plot of stress against number of dimensions

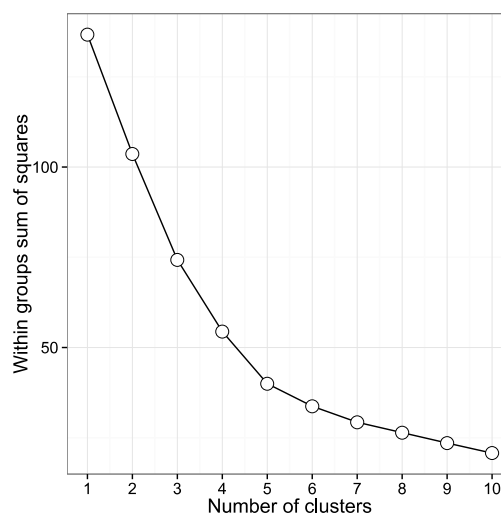


FIGURE 3.2.3: A scree plot of within-group sum of squares against number of clusters

the 4-dimensional data. The appropriate number of clusters was decided after investigating a scree plot of within-group sum of squares against number of groups (see Figure 3.2.3, suggesting 5 relation classes.⁵

Each panel of Figure 3.2.4 presents the distribution of compounds on a 2D subspace of the full 4D space with clusters color-coded. The contours on the upper right panels indicate specific densities. The figure, especially the distribution of compounds on a 2D subspace spanning Dim 1 and Dim 4, suggests that those 5 groups discovered by *k*-means clustering were relatively well separated.

Hierarchical organization of compound relations

To investigate if compound relations are hierarchically organized, *k*-means clustering was applied to each of 5 groups of compounds separately. If we can find well-separated subclusters within a cluster, it suggests hierarchical organization of the relation space. It turned out that at least 2 of 5 clusters (Class 1 and Class 4) seem to have clearly separated subgroups (see Figure 3.2.5 and 3.2.6).

The first subgroup (N = 31) of Class 1 contains “winter season, winter storm, March sales, weekend boredom, summer travel, evening journey, morning cloud, summer months, sunset prayer, lifetime achievement, summer sports, autumn rain, swamp forest, morning commercial, spring party, weekday life, college adventure, summer safari, Thanksgiving guest, winter bird, night battle, midnight train, adolescence turmoil, weekend lodge, evening hours, evening grove, midnight headache, autumn trail, family problem, childhood dream, April homework,” suggesting that this subgroup instantiates the H-DURING-M relation. Some cases (e.g., “family problem,” “swamp forest”) seem to be misclassification.

⁵Five classes consist of 89, 51, 78, 69, and 97 transparent compounds, respectively.

The second subgroup (N = 58) of Class 1 contained “ghetto turmoil, ice hole, street riot, hill trails, building roof, castle hall, office friendship, wilderness road, boat adventure, river sports, water bird, prairie adventure, island bird, road trip, beach party, kennel puppy, sea-

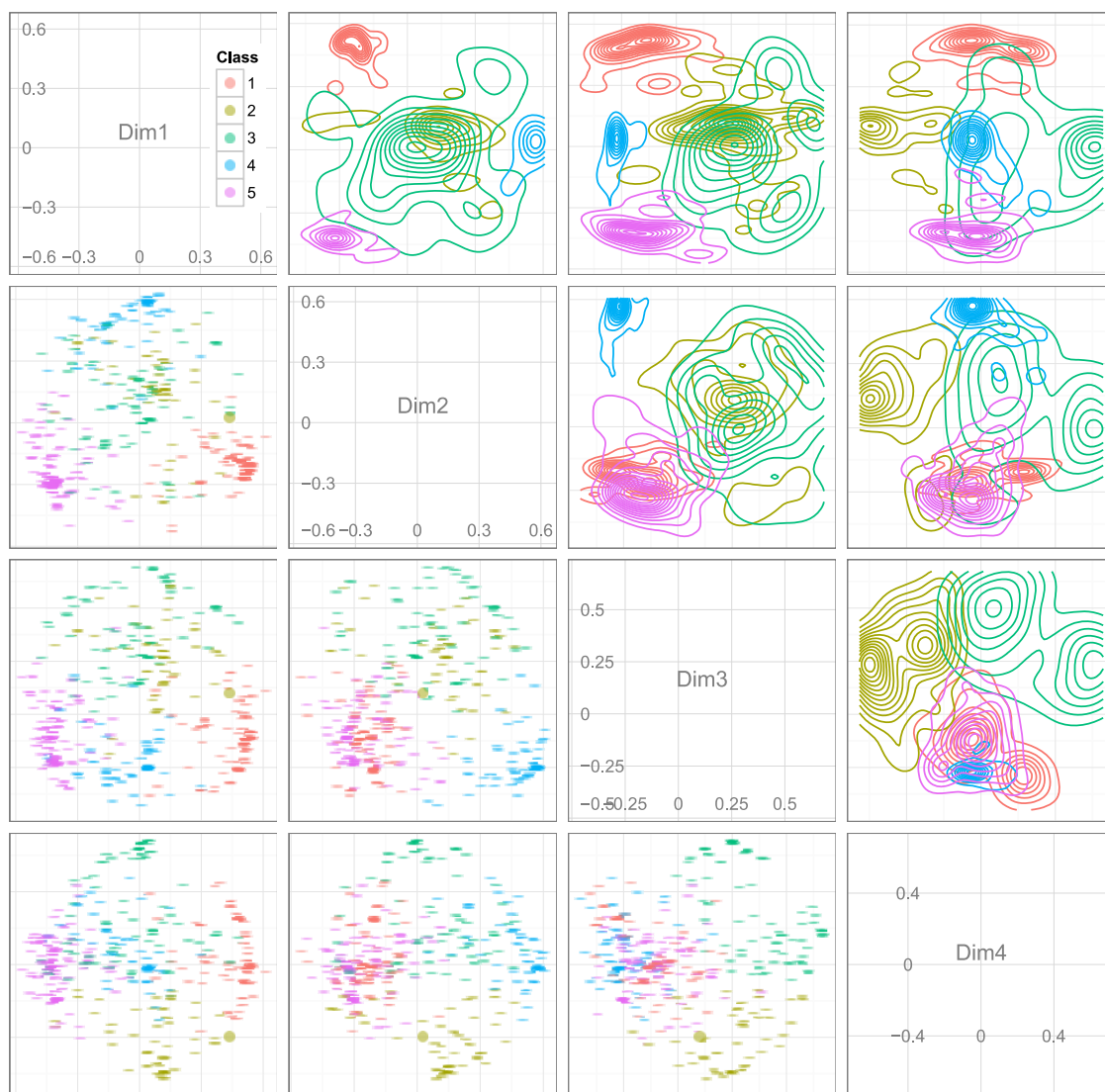


FIGURE 3.2.4: Distribution of 384 transparent compounds on a 4D space. Each point corresponds to a particular compound; clusters are color coded (Class1 = red, Class2 = yellow, Class3 = green, Class4 = blue, Class5 = purple). Density distributions are shown in contours.

side bungalow, table bowl, island life, sea battle, landfill bird, ground floor, brain disease, mountain lion, school achievement, classroom tension, university grove, spleen disease, field mouse, surface tension, attic floor, testtube baby, city wall, Iraq war, space journey, pocket money, cucumber disease, ocean cloud, store clothes, shirt collar, country factory, church fire, air ball, sea breeze, highland forest, cave prayer, desert lizard, hand scar, court-room action, kitchen door, dog virus, county land, outside situation, water snake, hotel room, ankle pain, mountain lodge, airport store,” suggesting that this subgroup roughly instantiates the H-LOCATED-AT-M relation. A few cases (e.g., “kennel puppy,” “dog virus”) seem to be misclassification. This subgrouping pattern is consistent with Levi (1978) that proposed a general relation class H-IN-M whose subclasses are H-IN:LOCATION-M and H-IN:TIME-M (see also, Warren, 1978).

The first subgroup (N = 48) of Class 4 contains “glass eye, plum wine, olive oil, rice paper, hydrogen bomb, leather album, cane sugar, peanut butter, plasma cloud, leather pants, sand dune, worker team, copper bottle, ion cloud, candy cigarette, wool jacket, stone wall, vegetable soup, grain alcohol, rubber shoes, paper money, metal money, corn chip, daisy chain, pumpkin pie, bronze statue, sugar cube, paper magazine, glass door, aerosol spray,

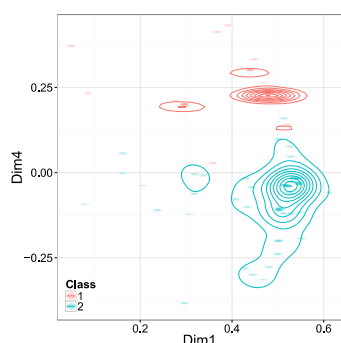


FIGURE 3.2.5: Four subgroups within Relation Class 1

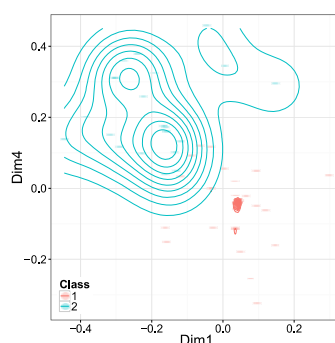


FIGURE 3.2.6: Two subgroups within Relation Class 4

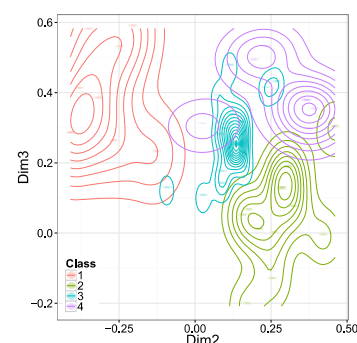


FIGURE 3.2.7: Two subgroups within Relation Class 2

coal dust, alligator leather, rye whiskey, steel helmet, cream sauce, copper coin, citrus lotion, mosquito cloud, lace handkerchief, apple cake, student committee, mountain range, chocolate bar, smoke signal, iron fence, oak lodge, straw roof, herb pills,” suggesting that this subgroup instantiates the H-MADE-OF-M relation. The second subgroup (N = 21) of Class 4 contained “fish farm, flower garden, salt lake, tree farm, nut bread, malaria mosquito, chimney roof, sound card, ice storm, protein drug, dolphin aquarium, walnut cake, pet family, dust storm, spa resort, peephole door, picture book, orange grove, sap tree, fruit tree, vitamin shampoo,” suggesting that this subgroup instantiates the H-HAS-M relation. Some cases in this subgroup are like “nut bread” and “vitamin shampoo,” suggesting why the two subgroups are grouped together to form Class 4. It is interesting that the H-MADE-OF-M group (corresponding to M-MAKES-H in Levi (1978)) was perceived more similar to the H-HAS-M group than to the H-MAKES-M group.

Subgrouping was clear in these two relation classes in the sense that each subgroup has a clear relation interpretation. But other relation classes could be divided into multiple subgroups. For example, Class 2 seems to have four subgroups (see Figure 3.2.7. The first subgroup (N = 9) of compounds (e.g., fish scale, government forest, library book, company store, lemon peel, tire rim, melon peel, family antique, apple cores) instantiates the M-HAS-H relation; the second group (N = 13) of compounds (e.g., bacon grease, court decision, people power, snow blindness, cocaine death, laugh wrinkle, explosion turmoil, tobacco ash, moth hole, air pressure, machine translation, oil money, water mark) instantiates the M-CAUSES-H or H-FROM-M relation; the third subgroup (N = 22) of compounds (e.g., future shock, birth pain, separation anxiety, rubber headache, juice stains, cigarette fire, home remedy, coffee nerve, government employment, pupil achievement, drug death, bullet scar, job tension, deficiency disease, fatigue headache, alumni money, wind burn, onion tear, heat rash, peer therapy, laugh hiccup, stage fright) instantiates the M-CAUSES-

H relation similar to the second subgroup; the fourth subgroup ($N = 7$) of compounds (e.g., cold crack, infection germ, accident weather, boom box, disease germ, trauma event, anxiety situation) instantiates the H-CAUSES-M relation except for “cold crack.” Although in Relation 2, subgrouping is not very clear, overall this class can be subgrouped into M-HAS-H and two CAUSES relations.

Relation Class 3 consists of the following compounds: cancer gene, suspense film, surprise attack, red-card foul, risk behavior, enemy strength, tear gas, accident carelessness, enforcement action, death battle, suicide bombing, disaster flick, sob story, flu virus, queen bee, box kite, sister node, citizen soldier, soldier ant, satellite nation, child actor, servant girl, star shape, trash fish, tree trunk, woman doctor, instantiating the H-CAUSES-M relation; love song, investment decision, energy emergency, horror movie, school album, mountain magazine, book party, abortion vote, tax law, insect homework, abortion problem, travel album, money prayers, history conference, sports magazine, copyright law, morphology lecture, finance law, wolf story, adventure story, torture law, math magazine, superhero movie, budget speech, physics homework, fertility disease, roughly instantiating the H-ABOUT-M relation; steam iron, pressure cooker, sports activities, time trial, ferry journey, gas stove, voice commercial, wind farm, ball sports, vacuum cleaner, coal stove, radio communication, voice vote, air brake, hand brake, song commercial, starvation diet, instantiating the H-USES-M relation; and other compounds like pole height, company equipment, entrance hall, party member, ball boy, color television, party life, pine tree, song bird.

Relation Class 5 consists of the following compounds: yacht club, coat store, rest chair, finger cymbals, freedom war, rescue equipment, wrinkle lotion, stock market, heat pants, cooking utensil, company asset, music box, juice bowl, investment benefit, time card, kid book, moisture shampoo, allergy pill, basketball season, safety wall, potion bottle, picture album, water pants, college town, fertility pill, vacation house, security lens, lightning rod,

warrior caste, baby chair, tennis racket, chat room, coast guard, union lawyer, stamina food, stamina soup, rain shoes, nose drop, cancer drug, dandruff shampoo, basket store, cranberry bowl, hair lotion, mud boots, health club, health diet, hunting land, bug spray, book club, dust goggle, wedding cake, bond paper, student magazine, vapor lock, fitness shoes, steak knife, stock yard, foam factory, automobile plant, wind jacket, sun umbrella, flash card, sand equipment, pest poisons, call box, reindeer land, baby fences, study lamp, tractor engine, jewel box, pet spray, chair doctor, fruit basket, baby doctor, burglar fence, heart drug, growth hormone, water wheel, bachelor room, horse doctor, graph paper, noise walls, beach ball, lifetime lawyer, sweat jacket, coke machine, measles vaccine, pool house, statue hall, pope lawyer, extension ladder, bicycle trails, widget factory, cough medicine, war club, jewel store, coffee break, suggesting that roughly the class as a whole instantiates the H-FOR-M relation.

3.2.3 Discussion

We need to be careful when interpreting the clustering result because *k*-means clustering returns the grouping result given a given number of groups regardless of how appropriate the grouping is. What we can say from the analysis is that compound relations are not randomly distributed in the relation space.

First, relations form a small number of dense clouds, suggesting that there are a finite number of relation classes each of which is well separated from other classes, supporting Hypothesis 2A. Second, within some of relation classes, several subgroups are found, supporting Hypothesis 2B that compound relations are hierarchically organized. Meaningful subgroups of compounds suggest that a subgroup as a whole is closer to another subgroup from the same relation class than to other relation classes. Two main results to-

gether support Hypothesis 2 that relational similarity is graded (at least at a group level) on a continuum.

3.3 Experiment 2

Relation priming refers to a phenomenon in which the comprehension of a compound (e.g., “coffee tension”) instantiating a certain relation R_1 (e.g., M-CAUSES-H) is facilitated after processing another compound instantiating the same relation R_1 (e.g., “coffee stain”) than after processing another compound instantiating a different relation R_2 (e.g., “coffee container”) instantiating H-HAS-M) (Gagné, 2001). Gagné (2001) argued that relation priming was observed only when prime and target compounds shared the same modifier noun or had highly similar modifier nouns (Gagné, 2002) while Estes and Jones (2006) argued that relation priming was observed even when modifier and head nouns constituting prime and target compounds were conceptually different. The debate is if relation representations are concept-dependent (Gagné, 2001, 2002) or concept-independent (Estes & Jones, 2006; Pickering & Ferreira, 2008). If relation priming is observed between two compounds that consist of different modifier and head nouns, it suggests the representation space of relations is separate from the representation of concepts. Based on the self-organizing treelet model, we hypothesize that relations are represented in a separate representation space (the relation units in the model).

Estes and Jones (2006) further proposed the graded relation priming effect hypothesis. Estes and Jones (2006) collected pairwise relational similarity rating scores for prime and target compound pairs and investigated the relation between pairwise relational similarity and the priming effect size. Based on a post-hoc regression analysis, they argued that the

amount of relation priming was correlated with the graded similarity score, even when lexical similarity between prime and compounds was statistically controlled.

In a typical relation priming paradigm (Estes & Jones, 2006; Gagné, 2001, 2002), participants were given a list of sensible or nonsense noun-noun combinations and asked to judge if a noun-noun combination is sensible or not as quickly and as accurately as possible. The task situation is clearly different from sentence comprehension. In this study, we wanted to test if offline relational similarity relationships influenced online compound comprehension in sentence processing so we used a self-paced reading paradigm. To introduce structural parallelism (Bock, 1986; Dubey, Keller, & Sturt, 2008; Frazier, Munn, & Clifton, 2000; Pickering & Ferreira, 2008), we presented compounds in a sentence carrier phrase with a coordination structure, “NN₁ and NN₂.” NN₁ is considered the prime and NN₂ is considered the target. Relational similarity between the prime and target compounds was manipulated based on the notion of relation hierarchy in a theory-driven way (see the Materials section).⁶ Following Estes and Jones (2006), we hypothesized that the amount of relation (or structural) priming would be a function of relational similarity (Hypothesis 2C).

3.3.1 Methods

Participants

Fifty-four undergraduate students of the University of Connecticut participated in a self-paced reading task for course credit. Three participants were excluded from further analyses because they self-reported a reading disability (N=2) or were a non-native speaker of

⁶Experiment 2 was run before the card sorting study. Thus, we could not use similarity rating scores from the sort task to construct the stimulus list. At that time, we followed a theory-driven way to construct the stimulus list and then planned to run manipulation check later (see the Materials section).

English (N=1). Another group of 30 participants participated in a pairwise similarity rating task for manipulation check (see Procedure).

Design & Materials

To study the effect of structural parallelism in comprehension, we used a coordinate structure to construct the following sentence frame, “[Name] [Verb] about [Prime Phrases] and [Target Phrase] in the [Time]” (e.g., “Zoe learned about rain shoes and dust goggles in the afternoon”). Target phrases were always noun-noun compounds and prime phrases were either noun-noun compounds or Adj + N phrases (e.g., “cute shoes”). In all sentences, the head nouns of the prime and target phrases were plural. We used a single-factor within-subject design in which the type of prime phrases (PrimeType) was manipulated across four levels in terms of structural similarity between prime and target phrases.

Consider a transparent compound *dust goggles* as target phrase which instantiates the H-FOR:PROTECT-AGAINST-M relation. In the no similarity (NoSim) condition, the prime was an Adj + N phrase (e.g., “cute shoes”) which is syntactically different from the target phrase. In the low similarity (LoSim) condition, the prime was a transparent noun-noun compound (e.g., “rubber shoes”) instantiating a different relation (e.g., H-MADE-OF-M) from the target. In the medium-level similarity (MedSim) condition, the prime was a transparent noun-noun compound (e.g., “fitness shoes”) instantiating a similar but slightly different relation (e.g., H-FOR:ENHANCE-M) from the target. In the high similarity (HiSim) condition, the prime was a transparent noun-noun compound (e.g., “headache pills”) instantiating a very similar relation (e.g., H-FOR:PROTECT-AGAINST-M).

For the purpose of constructing four primes for each target compound, we chose target noun-noun compounds such that they were classified into one of four relation classes

(FOR, IN, CAUSE, HAVE) which, according to other researchers, seem to have at least two subtypes. For example, Downing (1977) pointed out that *headache pills* and *fertility pills* instantiate two different relations although they were classified into the same class (FOR) in Levi (1978). It seems reasonable to think that the FOR relation class consists of at least two subtypes. Although the H-DURING-M (e.g., *summer safari*) and H-LOCATED-AT-M (e.g., *mountain squirrel*) relations were treated as different relations in Gagné and Shoben (1997), Levi (1978) and Warren (1978) treated them as two subtypes of the same class (IN) (see also, Jackendoff, 2010). Similarly, two CAUSES relations (H-CAUSES-M [*flu virus*] and M-CAUSES-H [*fatigue headache*]) and two HAS relations (H-HAS-M [*fruit basket*] and M-HAS-H [*company asset*]) were treated as different relations in Gagné and Shoben (1997) but we treated them as subtypes of a relation class based on Levi (1978). Two relations which are subtypes of a relation class were used to construct pairs of compounds for the medium-level similarity condition.

Forty-eight target noun-noun compounds and 48 quadruples of prime phrases were constructed (see Appendix B). Whenever possible, each quadruple was constructed to share the same head noun. Thirty-two (of 48) quadruples of primes shared the same head noun. Also we tried to use different constituent nouns between prime and target phrases. The modifier similarity and head-noun similarity between prime and target phrases was extracted from the latent semantic analysis (LSA; Landauer & Dumais, 1997) database on the LSA website (<http://lsa.colorado.edu/>).⁷ The average modifier similarity S_M was .096 (SD = .093) and the average head-noun similarity S_H was .109 (SD = .104). Linear mixed-effects modeling was used to test if S_M or S_H is a function of PrimeType. PrimeType was Helmert coded to compare each level of PrimeType to the mean of the subsequent levels.

⁷Specifically, we used the Matrix Comparison tool with the default setting to get the LSA similarity scores for modifier pairs and head-noun pairs.

The analysis revealed that S_M in the no similarity condition was greater than the measure averaged across the other three conditions ($b = -0.039$, $SE = 0.014$, $t(140.83) = -2.74$, $p = .007$), suggesting that modifier similarity was lower in noun-noun compound primes. S_M was not different across three compound prime conditions (Lo-, Med-, and HiSim). S_H was not a function of PrimeType, which makes sense given that many quadruples of prime phrases shared the same head nouns. Given the direction of the effect which works against the predicted patterns, this systematic difference is not a problem. Moreover, in the analysis of reading time data, S_M and S_H will be used as covariates to statistically control the contribution of lexical similarity to the amount of priming.

192 pairs of prime phrases and target compounds were separated into four lists such that (1) four primes paired with the same target compound were distributed across four lists and (2) each list had 12 trials per condition.

For a pairwise relational similarity rating task (see Procedure), 144 pairs of compounds used in the low-, medium-level, and high similarity conditions were separated into three lists such that (1) three prime compounds associated with the same target compound were distributed across three lists and (2) each list had 16 pairs of compounds from each of three conditions.

Procedure

In a sentence reading experiment, participants read sentences word-by-word as in Experiment 1. Once they read a sentence, they were given a prime or target noun phrase that occurred in the sentence and asked to paraphrase it by typing one or more verbs optionally followed by a preposition that can substitute the dots in “[N1] [N2] is a(n) [N2] that ... [N1]” (Nakov, 2008). For example, participants read a sentence “Sophia thought about

allergy pills and cough medicines in the morning” and then were given “Cough medicines are medicines that ... cough(s).” Typically participants substituted the blank with “cure,” “heal,” “prevent,” “suppress,” and so on. The task took about 20 minutes.

For manipulation check, another group of participants was given a pairwise relational similarity rating task (Estes & Jones, 2006). In this task, participants were given one of three versions of booklets containing 48 pairs of compounds and rated how much relationally similar each pair of compounds is on a 7-point scale (1 - *not at all relationally similar*, 7 - *very relationally similar*). The instruction for this task is presented in Appendix F. It is well known that similarity judgment is sensitive to the presentation order (Tversky, 1977). Given the order of occurrence in sentences used in the self-paced reading task, the prime compound was always presented before the target compound. Up to 12 participants were tested in the same place.

3.3.2 Results

Pairwise relational similarity rating

An average pairwise relational similarity score was computed from 10 participants for each pair of noun-noun compounds used in the low, medium-level, and high similarity (LoSim, MedSim, HiSim) conditions in the self-paced reading experiment.

The mean of pairwise relational similarities in each relation class is presented in Figure 3.3.1. It turned out that the prime-target pairs of the HAVE class did not satisfy the constraint that relational similarity (RS) should be ordered such that $RS(\text{LoSim}) < RS(\text{MedSim}) < RS(\text{HiSim})$.⁸ It seems that the IN-class compound pairs did not satisfy

⁸For the HAVE-class target compounds, prime compounds in the low similarity condition were chosen such that they instantiated the MADE-OF, IN:Place, IN:Time, or FOR relation. The analysis of the sorting

the constraint, either, suggesting that two relations IN:Place and IN:Time are perceived as quite different relations.⁹ Because the HAVE relation class looked very different from other three relation classes, we exclude the relation class from further analysis.

Because the goal in Experiment 2 was to test if the amount of priming in online compound comprehension is graded due to gradual structural parallelism between prime and target compounds, it was important to construct the pairs such that $RS(LoSim) < RS(MedSim) < RS(HiSim)$.

We used a linear mixed-effects model to test if the remaining items satisfied the constraint. The model concerned PrimeType as a fixed-effect term and by-item random intercepts. PrimeType was backward difference coded such that the mean relational similarity for one level of PrimeType was compared to the mean relational similarity for the prior adjacent level. Relational similarity was significantly higher in the medium-level similarity

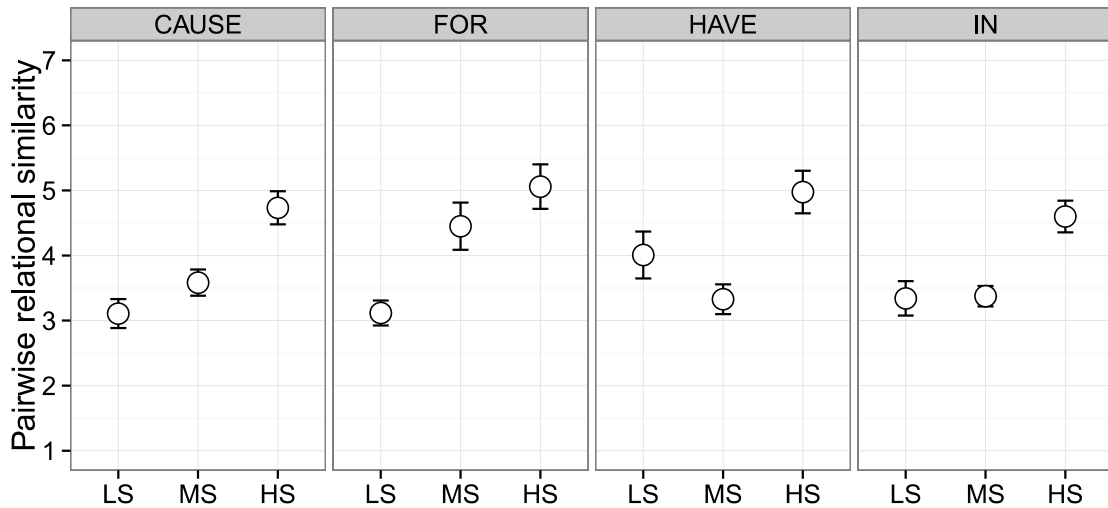


FIGURE 3.3.1: Mean pairwise relational similarity score per PrimeType, separated by relation class (N=10). LS = Lo Similarity, MS = Medium Similarity, HS = High Similarity)

data suggests that the H-MADE-OF-M relation was similar the H-HAS-M relation.

⁹In the analysis of card sorting, however, we observed the subgroups of two IN relations.

condition than in the low similarity condition ($b = 0.614$, $SE = 0.187$, $t(70.0) = 3.282$, $p = .0016$). Relational similarity was significantly higher in the high similarity condition than in the medium-level similarity condition ($b = 0.994$, $SE = 0.187$, $t(70.0) = 5.317$, $p < .0001$). The analysis suggests that PrimeType was manipulated as intended once the HAVE-class items were excluded.¹⁰

Self-paced reading

Before analyzing word reading times in sentence reading, we investigated how accurately participants paraphrased prime and probe phrases. The author classified participants' responses into correct (intended) or incorrect (not-intended) responses. Four participants whose mean accuracy in the paraphrase task was lower than 0.65 were excluded from further analyses.¹¹ Item mean paraphrase accuracy was not considered because only a very small number of participants paraphrased a particular noun-noun compound so the measure was not reliable.

Word reading times were log-transformed and then trimmed in the same way as in Experiment 1. In other words, log reading times that were greater than 2.5 SDs from the average per word region per individual were trimmed to the values, in order not to lose data points. Reading times that were faster than 50 ms were set to 50 ms. With trimmed log reading time data, individual mean log reading times were computed. One exceptionally fast reader was excluded from further analyses; the individual's average log reading time was greater than 2.5 SDs below the average of participants. For counterbalancing, only the first 10 participants were chosen from each version of the stimulus lists. The following

¹⁰When the relational similarity estimated from the card sorting data was used, we observed the same, but more reliable pattern. The correlation between two similarity measures was .623, $t(142) = 9.48$, $p < .0001$.

¹¹The criterion was decided after checking the distribution of individual mean paraphrase accuracy.

analyses were based on these 40 participants. The mean word reading time (in msec) is presented in Figure 3.3.2.

The log reading times were analyzed in two steps as in Experiment 1. First, residual log reading times were computed from a linear mixed-effects model into which the number of letters (WordLen), the logarithm of trial number (LogTrialNum), and the factor (Exp) distinguishing between experimental and filler trials entered with by-subject random intercepts. As expected, reading was faster on shorter words than on longer words ($b_{\text{WordLen}} = -0.021$, $SE = 0.0007$, $t(38410) = 31.077$, $p < .00001$). Reading was faster at later trials than at earlier trials ($b_{\text{LogTrialNum}} = -0.3448$, $SE = 0.0037$, $t(38410) = -93.570$, $p < .00001$). The effect of Exp was not significant ($b = -0.004$, $SE = 0.003$, $t(38410) = -1.381$, $p = .167$).

The residual log reading times were averaged across the region of interest, “[target com-

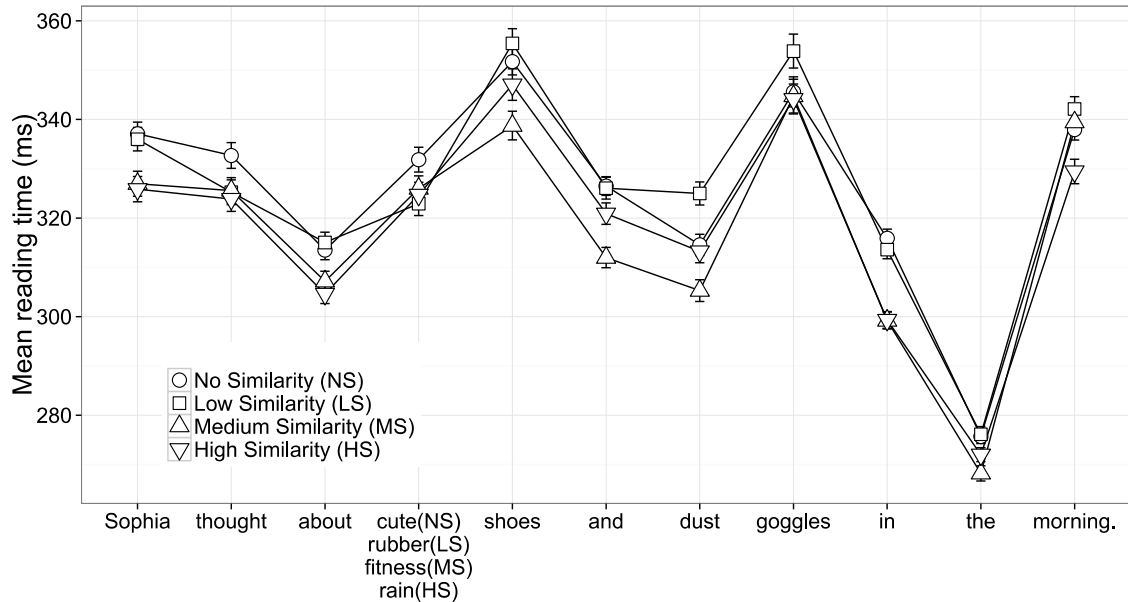


FIGURE 3.3.2: Mean reading time (ms) per word region

TABLE 3.3.1: Summary of fixed-effect terms ($N = 1211$, $-2LL = -1178.035$). LoSim = low similarity, MedSim = medium-level similarity, HiSim = high similarity, C1-C3 = specific contrasts, S_M = LSA modifier similarity, S_H = LSA head-noun similarity, $\log RT(\cdot)$ = word log reading time.

Terms	<i>b</i>	<i>SE</i>	<i>df</i>	<i>t</i>	<i>p</i>
Intercept	-1.2320	0.0971	847.5	-12.695	< .0001
C1: (Lo-, Med-, HiSim) - NoSim	-0.0096	0.0095	81.4	-1.011	.3152
C2: (MedSim, HiSim) - LoSim	-0.0277	0.0103	90.1	-2.697	.0084
C3: HiSim - MedSim	-0.0100	0.0123	98.1	-0.815	.4169
S_M	-0.0067	0.0444	104.6	-0.150	.8809
S_H	0.0227	0.0466	32.8	0.487	.6298
$\log RT(\text{'and'})$	0.0283	0.0145	1193.0	1.944	.0521
$\log RT(\text{PrimeModifier})$	0.0756	0.0133	1194.0	5.665	< .0001
$\log RT(\text{PrimeHead})$	0.1049	0.0157	1187	6.692	< .0001

pound] in the” in this experiment. We included the “in the” regions to consider the possible spill-over effect. Then, the average residual log reading time was analyzed by using a linear mixed-effects model that had PrimeType, LSA modifier similarity (S_M) and LSA head-noun similarity (S_H), log reading time at each of the three previous words (“[prime phrase] and”) as fixed-effect terms with by-subject intercepts, by-item intercepts, and their interactions with PrimeType. LSA similarity measures were included to statistically control possible lexical priming between prime and target phrases. The log reading times at each of previous word regions were included to control expected spill-over effects from those regions to the region of interest. PrimeType was Helmert coded. Based on the manipulation check for relational similarity, the trials in which the target compounds instantiated HAVE relations were excluded from this analysis. Also the trials in which participants misparaphrased either prime or target compounds were excluded from further analyses. The summary of the fixed-effects is presented in Table 3.3.1.

The two lexical similarity measures (S_M and S_H) did not make significant contributions. On the other hand, the log reading times at the previous word regions had significant effects

on the log reading time at the critical region. Their positive coefficients suggest that the slower participants read a prime phrase, the slower they read a target compound, indicating the spill-over effect.

Our interest is in the effect of PrimeType when other variables were statistically controlled. Compound comprehension (measured by average residual log reading time) in the low similarity condition was not different from the other three conditions (Lo-, Med-, HiSim) ($b_{C1} = -0.0096, p > .315$), indicating that there was no evidence for simple syntactic priming. However, compound comprehension in the low similarity was significantly slower than in the medium-level and high similarity conditions ($b_{C2} = -0.0277, p < .009$), suggesting positive structural priming when prime and target compounds instantiate similar relations. Compound comprehension speed in the medium-level and high similarity conditions were not statistically different ($b_{C3} = -0.0100, p > .416$).

3.3.3 Discussion

The result pattern is as follows. First, RT_{NoSim} was not different from RT_{LoSim} , RT_{MedSim} , RT_{HiSim} . This is because RT_{NoSim} was not statistically different from RT_{LoSim} . It suggests that having the same syntactic form (N + N) is not enough to prime another compound, rejecting a simple syntactic priming account. Second, we replicated relation priming reported in previous studies but in sentence reading: RT_{LoSim} was greater than RT_{MedSim} and RT_{HiSim} . Given that lexical similarity between prime and target compounds was low and moreover statistically controlled, the result suggests that the representation space of relations is separate from the representation of concepts, supporting Estes and Jones (2006) and the self-organizing treelet model. Third, however, we failed to support Hypothesis 2C (Graded Structural Parallelism); RT_{MedSim} was not different from RT_{HiSim} .

Regarding the failure of detecting the graded priming effect, we propose three accounts. First, the relationship between relational similarity and the amount of priming would be nonlinear. For example, the amount of priming might be a sigmoid function of relational similarity such that the abrupt change in priming effect happens between low similarity and medium-level similarity conditions. Second, the self-paced reading task might be too coarse to capture the graded effect. It is worth using more sensitive methods like eye tracking to test the graded structural parallelism hypothesis.

Third, participants might not comprehend prime compounds fully before they encounter target compounds. In Experiment 2, prime and target compounds were separated by only one word “and.” But we observed the spill-over effect from the target head noun to the following words in compound comprehension in Experiment 1. It is likely that participants did not fully process the meaning of a prime compound before they moved to the target compound in self-paced reading. Note that the offline measure of relational similarity is a function of the distance between the goal state given a prime compound and the goal state given a target compound. However, the priming effect in the generalized state space model or the self-organizing treelet model would be a function of the distance between the state right before the target compound input and the goal state given the target compound. If participants have not fully processed a prime compound before they encounter a target compound, the state right before the target compound input must be different from the goal state given the prime compound. We can think of the following scenario from the self-organizing treelet model. Every state change takes time. When participants read a prime compound, the relation state moves toward the goal state given the compound. But participants might decide to read the next words before the relation state arrives at the goal state. In this situation, the actual distance associated with state change stimulated by the target compound input is not a simple function of relational similarity. Rather, we

need to consider where the relation state is right before the target compound is presented. To explain no difference between medium-level and high similarity conditions, we need to think about the topology of the target states given the prime and target compounds. In those two conditions, prime compounds instantiate two subclasses (e.g., H-IN:LOCATION-M and H-IN:TIME-M) of a relation class that would be located close to each other in the relation space. Then, the state change responding to a prime compound would follow similar trajectories especially at the beginning in both medium-level and high similarity conditions. If the target compound is presented before the relation states are following similar trajectories, then the model naturally predicts similar amounts of priming effects.

Regardless of which account is true, we argue for the graded nature of relation representations because offline measures (relational judgment or card sorting) supports the continuous relation space hypothesis. Once we accept the hypothesis, the data should be interpreted as revealing a non-linear relationship (between relation similarity and the effect size of priming). It suggests that processing difficulty is not a simple function of the distance between two states (for example, the end state after processing a prime compound and the goal state of a target compound, (Devereux & Costello, 2006)). We emphasize again the importance of considering processing dynamics in online compound comprehension. After presenting the results of Experiment 3, we will present a simulation study (Simulation 2) that suggests feedback dynamics between activating units plays a critical role.

Chapter 4

A single mechanism view of noun-noun compound processing

4.1 Introduction

In Chapters 2 and 3, we focused on transparent noun-noun compounds (e.g., “mountain magazine”) that can be understood apparently compositionally. However, there are many opaque compounds that have idiosyncratic meanings (e.g., "seahorse"). According to the words-and-rules theory (Pinker, 1999), the meanings of opaque compounds are stored into and retrieved from the mental lexicon but the meanings of unfamiliar transparent compounds are computed on the fly by the rule system. On the other hand, the self-organizing treelet model embodies an alternative view: both types of compounds are processed by a single mechanism and represented in the same mental space. In this study, we report a priming experiment to test Hypothesis 3 that transparent and opaque compounds are represented in the same relation space.

More specifically, in this experiment, we investigate relational/structural priming between lexicalized and novel compounds. Consider three models: the words-and-rules theory, a vector space model with no feedback dynamics, and the self-organizing treelet model.

According to the words-and-rules theory, opaque compounds are processed by a lexical route and transparent compounds are processed by a rule route. To make a prediction on relation priming, let us suppose that processing with the lexical route makes the route more accessible and its competing rule route less accessible. Then, the words-and-rules theory will predict negative priming between transparent and opaque compounds. But the theory makes the same prediction about priming between any idiosyncratic expression and any compositional expression priming happens not at a particular expression level but at the route or mechanism level. For example, the same amount of negative priming is expected between a compositional Adj + N phrase and an opaque noun-noun compound; and between a compositional compound and an opaque compound because the comprehension of the prime phrase requires using the rule route in both cases.

A vector space model with no feedback dynamics predicts that the degree of relational priming is a function of the distance between the representations of the lexicalized and novel compound. Together with Experiment 2, this vector space model predicts the same relationship between distance and processing difficulty. Given that we observed positive priming between transparent compounds instantiating similar relations, a reasonable prediction is that there will be positive priming between transparent and opaque compounds instantiating similar relations.

In a self-organizing treelet model, the result pattern depends on specific feedback dynamics. The model considers not just the distance between two states but also the rate of state change or the path that the state travels along, both of which are determined by weight parameters and specific linguistic inputs. Before making a specific prediction about prim-

ing between transparent and opaque compounds, consider what parameter setting is likely. The key is that component nouns of opaque compounds can freely combine with other nouns to form transparent compounds instantiating various canonical relations. But the relation state should arrive at a particular point (corresponding to an idiosyncratic relation) for a particular combination of the two component nouns of the opaque compound. The relation units in the model should receive bottom-up supports to both multiple canonical relations and a particular idiosyncratic relation. To resolve the ambiguity in the relation state space, the model needs strong inhibitory connections between the idiosyncratic relation and other canonical relations.

Recall that, in Chapter 3, we argued the relation space is hierarchically organized. A way of embodying a hierarchy of relations is to develop the representation of relations such that more similar relations share more relation features and less similar relations share less relation features as in a parallel distributed processing model of concept representation (c.f., McClelland & Rogers, 2003) in which concepts distinguished at more specific levels (e.g., “canary” and “robin”) share more semantic features while concepts distinguished at more general levels (e.g., “plant” and “animal”) share less semantic features. For example, we can think of the following system: a relation unit represents a general noun-noun relation. Another relation unit represents a more specific but still general relation (e.g., H-IN-M). Third and fourth relation units represent even more specific relations, TIME and LOCATION, respectively. In this system, two similar relations, H-IN:TIME-M and H-IN:LOCATION-M, share the first two relation features. Some relation units represent idiosyncratic relations. In this situation, an efficient solution to resolve the ambiguity between a target idiosyncratic relation and all canonical relations supported by each of component nouns is to develop a strong inhibitory connection between the idiosyncratic relation feature and the general noun-noun feature. If it is true, the model predicts “negative” prim-

ing between transparent and opaque compounds; the model predicts the comprehension of a transparent compound will be slower after processing an opaque compound, and vice versa. In this case, the model predicts a rather categorical negative priming effect. However, if the model develops inhibitory connections between the target idiosyncratic relation feature and more concrete relation features (something like H-IN-M or H-MADE-OF-M), then the effect size of negative priming can be graded.

4.2 Experiment 3

4.2.1 Methods

Participants.

Sixty-eight University of Connecticut undergraduate students participated in a self-paced reading experiment for course credit. Four participants were excluded from further analyses because they were non-native speakers of English (N=2), reported reading disability (N=1), or were an exceptionally slow reader¹ (N=1). Four more participants were excluded from further analyses for counterbalancing. Thus, the following analyses were based on sixty participants.

Design & Materials

We used a 2 x 3 mixed factorial design in which TargetType was instantiated at two levels (Transparent [TR] vs. Opaque [OP]) and PrimeType was manipulated across three levels

¹The participant's mean log reading time was greater than 2.5 SDs away from the average of individual mean log reading times.

TABLE 4.2.1: Examples of prime and target (*italics*) compounds. OP = opaque compounds, TR = transparent compounds, NS = no similarity, LS = low similarity, HS = high similarity.

TargetType	PrimeType	Prime1	Prime2	Target
OP	NS	cheap jackets	cute shoes	sandcastles
	LS	stock yards	bachelor rooms	sandcastles
	HS	glass doors	leather pants	sandcastles
TR	NS	rickshaws	scallops	leather pants
	LS	birdhouses	cupboards	leather pants
	HS	snowballs	sandcastles	leather pants

(No similarity [NS], Low similarity [LS], and High similarity [HS]). Examples of prime and target compounds are presented in Table 4.2.1. The prime and target compounds were presented in the following sentence frame: “[Name] / [Verb] about / [Prime1], / [Prime2], / and / [Target] / in the / [Time].” (e.g., *Sophia thought about glass doors, leather pants, and sandcastles in the morning.*) The slashes indicate the separation of frames in a moving-window self-paced reading task and were not displayed on the screen. Unlike Experiment 2, in this experiment, each frame contained one or two words.

In this experiment, we presented two primes of the same kind before the target compound (e.g., “[glass doors], [leather pants]. and [sandcastles]”) in all six conditions because we expected that repeating the same type of construction would enhance the amount of structural priming.

Consider the conditions in which the target compound is a transparent compound (e.g., “leather pants”). In the no similarity condition, primes were monomorphemic nouns (e.g., “rickshaws,” “scallops”). In the low similarity condition, primes were opaque compounds (e.g., “birdhouses,” “cupboards”) which instantiate a different relation (e.g., H-FOR-M) from the target. In the high similarity condition, primes are opaque compounds (e.g., “snowballs,” “sandcastles”) which instantiate the same relation (e.g., H-MADE-OF-M) as

target.

Now consider the conditions with an opaque compound (e.g., “sandcastles”) as target. In the no similarity condition, primes were Adj + N phrases (e.g., “cheap jackets,” “cute shoes”). In the low similarity condition, primes were transparent compounds (e.g., “stock yards,” “bachelor rooms”) which instantiate a different relation (e.g., H-FOR-M) from target. In the high similarity condition, primes were transparent compounds (e.g., “glass doors,” “leather pants”) and instantiate the same relation (e.g., H-MADE-OF-M) as the target.

We used the card sorting data reported in Chapter 3 to assign compound pairs into the low similarity and high similarity conditions. The average relational similarity between each of prime compounds and the target compound was 0.091 in the low similarity condition and 0.725 in the high similarity condition.

We constructed 36 quadruples of compounds each of which consists of two transparent and two opaque compounds that instantiate similar relations (e.g., “glass doors,” “leather pants,” “snowballs,” “sandcastles”) from the card sorting data. The high similarity condition items were constructed by choosing two opaque and one transparent compounds or two transparent and one opaque compounds from each quadruple. The low similarity condition items were constructed by pairing an opaque (or a transparent) compound with a pair of transparent (or opaque) compounds from a different quadruple instantiating a different relation. Materials used in Experiment 3 are presented in Appendix C.

For each of two TargetType conditions, three different lists were constructed such that (1) the prime pairs associated with the same target compound were distributed across different lists and (2) each list had 12 trials per condition.

TABLE 4.2.2: Mean sensibility rating scores and their standard deviations in parentheses. OP = opaque compounds, TR = transparent compounds, NS = no similarity, LS = low similarity, HS = high similarity.

TargetType	PrimeType		
	NoSim	LoSim	HiSim
OP	3.06 (0.90)	2.93 (0.97)	2.98 (0.95)
TR	2.52 (0.90)	2.68 (0.95)	2.85 (0.81)

Procedure

In a self-paced reading task, participants read sentences frame by frame and then rated how sensible each sentence was on a 5-point scale (1: *Makes no sense at all*, 5 : *Makes perfect sense*).² We did not use the structured paraphrase task (used in Experiment 2) because it does not make sense for opaque compounds in which component concepts need to be changed in many cases. For example, "seahorse" is not a horse that is located in the sea. The sensibility rating task was used to make participants involved in reading and avoid using nonsense noun-noun combinations or sentences. The experiment took about 15 minutes.

4.2.2 Results

Sensibility rating

Mean sensibility rating scores and their standard deviations (in parentheses) are presented in Table 4.2.2. A linear mixed-effects model was used to analyze trial-level sensibility rating. The model contained PrimeType and TargetType as fixed-effects terms. By-subject and by-item random intercepts and their interactions with PrimeType were considered as

²We did not use the paraphrase task used in Experiment 2 because the task was not appropriate for lexicalized compounds.

TABLE 4.2.3: Summary of fixed-effects terms (N = 2160, -2 LL = 5979.6)

Terms	<i>b</i>	<i>SE</i>	<i>df</i>	<i>t</i>	<i>p</i>
Intercept	2.8343	0.1169	64.12	24.254	< .0001
C1: (HiSim, LoSim) - NoSim	0.0701	0.0733	187.79	0.956	.3401
C2: HiSim - LoSim	0.1097	0.0847	187.79	1.296	.1966
TargetType	0.1528	0.1169	64.12	1.307	.1958
C1 x TargetType	-0.1729	0.0733	187.79	-2.358	.0194
C2 x TargetType	-0.0597	0.0847	187.79	-0.705	.4815

well. PrimeType was Helmert coded and TargType was effect coded. The summary of fixed-effect terms is presented in Table 4.2.3. The analysis revealed the interaction between Contrast 1 (C1) and TargetType ($b = -0.173$, $SE = 0.073$, $t(187.8) = -2.358$, $p = .0194$).

Self-paced reading

Frame reading times were log-transformed and then trimmed in the same way as in Experiment 1 and 2. Log reading times that were greater than 2.5 SDs from the average per word region per individual were trimmed to the values and log frame reading times that were shorter than 50 ms were trimmed to 50 ms. With trimmed frame log reading time data, individual mean log reading times were computed. One participant who read words exceptionally slowly was excluded from further analyses; the individual mean log reading time was lower than 2.5 SDs from the average of participants. For counterbalancing, only the first 10 participants were chosen from each version of the stimulus lists. The following analyses were based on these 60 participants. The mean word reading time (in msec) is presented in Figure 4.2.1.

The log reading times were analyzed in two steps as in Experiment 1. First, log reading times were regressed on the number of letters in each frame (Nletter), the number of words in each frame (Nword), the logarithm of trial number (LogTrialNum), TargetType, and

the factor (Exp) distinguishing experimental and filler trials, using a linear mixed-effects model with by-subject intercepts. TargetType was included because the number of words in a sentence was systematically different across two TargetType conditions. The effects of Nletters, WordLen, LogTrialNum, TargetType were statistically significant ($b_{Nword} = -0.0724$, $SE = 0.0048$, $t(30048) = -15.144$, $p < .00001$; $b_{Nletter} = 0.0376$, $SE = 0.0007$, $t(30048) = 55.171$, $p < .00001$; $b_{TargetType} = -0.1707$, $SE = 0.0613$, $t(58) = -2.783$, $p = .0073$; $b_{LogTrialNum} = -0.2875$, $SE = 0.0053$, $t(30048) = -54.042$, $p < .00001$) while the effect of Exp was not significant ($b = -0.0061$, $SE = 0.0042$, $t(30048) = -1.434$, $p = .15158$).

In the second step, the residual log reading times from the first step were averaged across the region of interest (“[Target] / in the”). Then, the average residual log reading

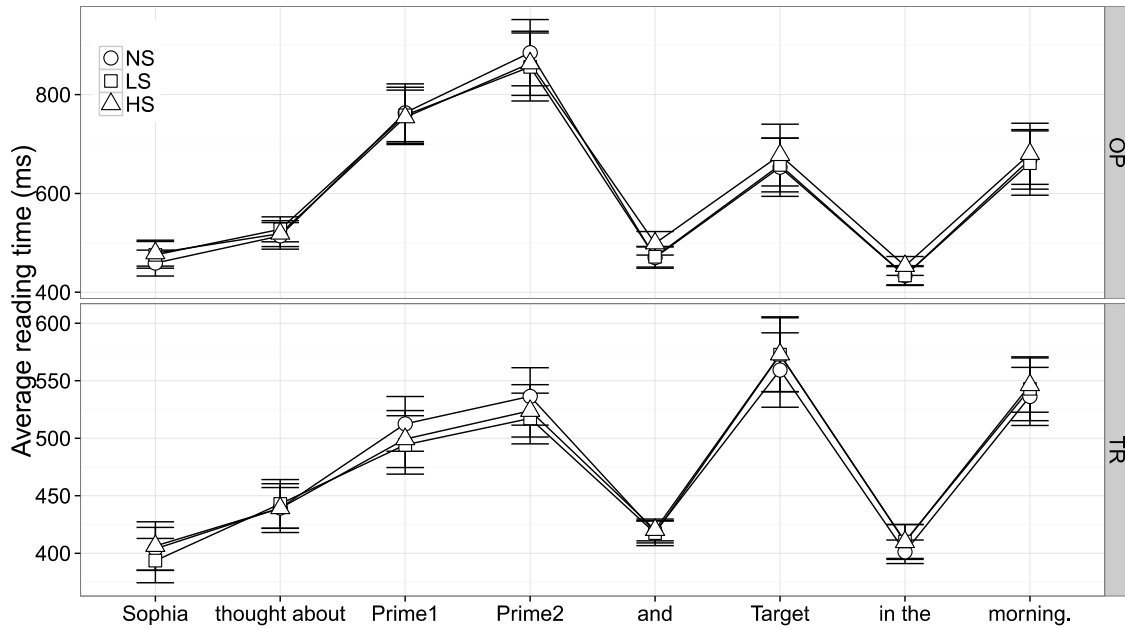


FIGURE 4.2.1: Mean reading time (ms) per word region. NS = no similarity, LS = low similarity, HS = high similarity, OP = opaque target compounds, TR = transparent target compounds.

time was analyzed by using a linear mixed-effects model that concerns PrimeType and TargetType as fixed-effect terms as well as by-subject intercepts, by-item intercepts, and their interactions with PrimeType. To control the spill-over effect from the previous word regions to the target region of interest, the log reading times of the previous three frames ($\log RT(\text{Prime1})$, $\log RT(\text{Prime2})$, $\log RT(\text{'and'})$) were included as fixed-effects as well. As in the analysis of sensibility rating, PrimeType was Helmert coded and TargetType was effect coded. The summary of fixed-effect terms is presented in Table 4.2.4. The effects of the log reading times at three previous frames (i.e., Prime1, Prime2, and “and”) were statistically significant ($b_{\text{Prime1}} = 0.0463$, $p = .0003$; $b_{\text{Prime2}} = 0.0779$, $p < .00001$; $b_{\text{and}} = 0.1423$, $p < .00001$), suggesting that processing difficulty at the previous frames was spilled over the target region. More importantly, when the spillover effect was statistically controlled, compound comprehension was statistically slower in the high similarity and low similarity conditions than in the no similarity condition ($b_{C1} = 0.0282$, $p = .0027$) but the comprehension speed was not different between the high similarity and low similarity conditions ($b_{C2} = 0.0060$, $p = .5781$), suggesting that the negative priming is categorical. The effect of TargetType was significant ($b = -0.0721$, $p < .00001$), indicating that reading was slower when target compounds were transparent compounds than when target compounds were opaque compounds. Given that opaque compounds are much more frequent than transparent compounds, the main effect of TargetType is likely to be a frequency effect.

TABLE 4.2.4: Summary of fixed-effects terms (N = 2160, -2 LL = -498.4)

Terms	<i>b</i>	<i>SE</i>	<i>df</i>	<i>t</i>	<i>p</i>
Intercept	-1.6519	0.1222	1467.0	-13.524	< .0001
C1: (HiSim, LoSim) - NoSim	0.0282	0.0094	2015.6	3.002	.0027
C2: HiSim - LoSim	0.0060	0.0109	2015.5	0.556	.5781
TargetType	-0.0721	0.0126	62.8	-5.741	< .0001
C1 x TargetType	-0.0019	0.0094	2015.1	-0.201	.8404
C2 x TargetType	0.0046	0.0108	2015.1	0.428	.6684
logRT(Prime1)	0.0463	0.0128	2103.3	3.611	.0003
logRT(Prime2)	0.0779	0.0132	2046.7	5.902	< .0001
logRT('and')	0.1423	0.0163	2113.1	8.734	< .0001

4.2.3 Discussion

Prosody priming?

Before evaluating three different models with regard to the result pattern, let us briefly consider an alternative account: the effect is prosody priming rather than relational/structural priming.

Admittedly, there is a systematic stress difference between transparent noun-noun compounds like “stone man” and opaque compounds like “snowman.” In the former case, “stone” and “man” receive equal stress; in the latter case, “snow” receives strong stress while “man” receives weak stress. Negative priming that we observed in Experiment 3 might stem from the different stress structure between prime and target compounds. However, the prime phrases when TargetType was opaque, Adj+N phrases in the no similarity condition and transparent noun-noun compounds in the low and high similarity conditions have the same stress pattern—strong stresses on both component words. Thus, the prosodic account cannot explain the effect of PrimeType. Also it is worth noting that we observed positive priming between transparent compounds in Experiment 2 only when prime and

target compounds instantiated similar relations. In Experiment 2, prime compounds in the low similarity condition had the same stress pattern as prime compounds in the medium-level and high similarity conditions.

Lynott and Connell (2010) investigated if the prosodic structure influences compound comprehension. Following Wisniewski and Love (1998), they constructed a set of compounds that prefer property-mapping interpretations and another set of compounds that prefer relation linking interpretations. Participants were given synthetic speeches of two-word phrases through speakers and then asked to type the phrase's interpretation. The prosodic structure of the synthetically generated compounds was manipulated such that the stress was on (1) modifier, (2) head, or (3) both nouns. While the comprehension of property-mapping type compounds was influenced by the prosodic manipulation, there was no effect of the prosodic structure on the comprehension of relation linking compounds. . Note that most of compounds used in Experiment 3 are relation linking compounds. At least, when target compounds were transparent compounds, target processing is not likely influenced by primes. Based on Lynott and Connell (2010), we seek an explanation in the semantic encoding relationships between compounds, ignoring the possibility that stress pattern plays a role. Further experimentation is needed to determine with certainty whether stress is an important factor.

Evaluation of models

The words-and-rules theory predicts negative priming between idiosyncratic expressions and compositional expressions. Thus, the theory predicts negative priming not just from transparent to opaque compounds in the low and high similarity conditions but also from Adj+N primes to noun-noun target compounds in the no similarity condition. Priming in

the opposite direction would be similar. Thus, the words-and-rules theory predicted no systematic conditional differences but we observed a different pattern.

Devereux and Costello (2006) represents compounds as a point in a vector space. Although they did not explicitly discuss opaque compound cases, it is reasonable to think that opaque compounds are represented with exemplars of transparent compounds in the relation space. As we described above, the way how the vector space model predicts processing times is to introduce a certain function that maps the distance between two states and processing times. The function can be nonlinear but must be monotonic. To explain Experiment 2 data, the model should assume the positive relationship between relational similarity (which is a function of the distance) and the amount of priming effect. Because there would be one such mapping function from distance to processing difficulty, the spatial model cannot explain both of positive priming between transparent compounds and negative priming between transparent and opaque compounds.

Neither the words-and-rules theory nor a simple similarity space model predicts the opposite priming effects in Experiments 2 and 3. In the next section we show how the dynamical framework offers a plausible mechanism. The explanation assumes one mechanism (contra Pinker, 1999) and it assumes a similarity space (in keeping with Devereux & Costello, 2006) but crucially it adds feedback dynamics.

4.3 Simulation 2

In this section, we present a simulation of the relational priming observed in Experiment 2 and 3. Instead of using a learning model, we constructed a hand-coded network based on theoretical assumptions. We ignored the top-down feedback connections from the relation

units to the conceptual units of the modifier and head nouns because they are not necessary to model the priming effects. The motivation is to construct a model as minimal as possible so the model’s dynamics is easy to understand and gives some insight into the empirical data.

Learning models are good because they offer an account of learning and can unify many phenomena by positing a single, very plastic mental mechanism. However, there are two challenges: (1) it is hard to get them to work; (2) even if they work, it is not always clear what they are saying, because the principles underlying the learned weights may be opaque (see discussion in Tabor, Cho, and Dankowicz 2013). Tabor (2000, 2003, 2009) describes a research endeavour in complex language processing with neural network models in which it was especially fruitful to first build a representational theory for the neural nets and then pursue a learning model. Here, we favor a similar approach. For Experiments 2 and 3, we provide a hand-coded model in order to identify a plausible goal of learning. In future work we plan to pursue a learning model.

4.3.1 A corpus

To simulate relation priming, we consider five relations. In this simulation, the model is not going to characterize the semantic qualities of these relations in any detail, but it will provide a simple approximation of the relationships between such relations. We labeled the five relations as IN, FOR, INe, FORe, and AN so that readers can easily consult intuition on natural language cases to which these are related. IN and FOR are canonical relations that IN-class and FOR-class transparent compounds instantiate.³ INe and FORe

³In fact, the self-organizing treelet model with a lot of relation units allows different compounds grouped into the same relation class (e.g., IN) or even the same subclass (e.g., IN:TIME) to instantiate slightly different relations. Given that we observed relation priming in Experiment 2 but the effect was not graded, we argue it is enough to distinguish among relations at this level of abstraction (e.g., IN vs. FOR). Because we need to

are idiosyncratic versions of IN and FOR relations. For example, “mountain squirrel” instantiates the IN relation while “seahorse” instantiates the INe relation. AN is the relation that Adj + N phrases instantiate. Here we assume that the relation space represents all possible syntactic/semantic relations between modifier and head.

In a free card sorting task, we presented some evidence for the hierarchical organization of relations. A way of implementing a hierarchical organization of relations in a connectionist network is to use distributed representations of relations. In McClelland and Rogers (2003), for example, some semantic features (e.g., move) are shared by all members of a general category (e.g., animal) while some semantic features (e.g., sing) are shared only by the members of a specific category (e.g., bird). Typically, similar concepts (e.g., robin and canary) that are classified into the same class (e.g., bird) share more semantic features. Two concepts (e.g., bird and fish) that are distinguishable at a more abstract level share less semantic features. McClelland and Rogers (2003) showed that a learning connectionist model can develop an apparently hierarchical organization of concepts in the hidden representation space by locating similar relations are close to each other. We applied the same idea to the representations of relations.

Five relations (IN, FOR, INe, FORe, and AN) are assigned distributed encodings across six relation units. The relation units $r_1, r_2, r_3, r_4, r_5, r_6$ represent a general relation feature (NN) shared by all transparent noun-noun compounds, a specific relation feature (RA) shared by the IN-class transparent compounds, a specific relation feature (RB) shared by the FOR-class transparent compounds, an idiosyncratic relation feature (RAe) possessed by an opaque compound that is relationally similar to the IN-class transparent compounds,

hand-code connection weights of the network, it is important to make the number of relation units minimal. Thus, we avoided considering more detailed distinctions among relations in this simulation. However, we point out that our modeling approach can extend to capture more fine-grained distinctions among relations and, in principle, can simulate the graded structural parallelism effect.

TABLE 4.3.1: Encoding of relations (NN = a general relation feature shared by all transparent compounds, RA and RB = specific relation features, RAe and RBe = idiosyncratic relation features used in opaque compounds, AN = a general relation feature shared by all Adj+N phrases)

Unit	Feature	Relations				
		IN	FOR	INe	FORe	AN
r_1	NN	1	1	0	0	0
r_2	RA	1	0	1	0	0
r_3	RB	0	1	0	1	0
r_4	RAe	0	0	1	0	0
r_5	RBe	0	0	0	1	0
r_6	AN	0	0	0	0	1

an idiosyncratic relation feature (RBe) owned by an opaque compound that is relationally similar to the FOR-class transparent compounds, a general relation feature shared by all Adj+N phrases, respectively (see Table 4.3.1).⁴

Note that the AN relation does not share any relation feature with other compound relations so the AN relation would be located distant from other relations. The IN-class and FOR-class transparent compounds share the general relation feature NN so two relations would be located closer to each other than to the AN relation. The IN–INe (or the FOR–FORe) relation pair shares a single relation feature RA (or RB) so the IN (or FOR) relation would be located closer to its idiosyncratic version, INe (or FORe), than to the idiosyncratic version of a different canonical relation, FORe (or INe). The design of relation representations was motivated by perceived relational similarity between transparent and idiosyncratic relations in the card sorting task (see Section 3.2 [p. 44]).

Each of three canonical relations (IN, FOR, and AN) is assumed to bind two semantic classes of nouns (or adjectives). So we created six classes of words, one of which is an

⁴In fact, a relation feature RAe (or RBe) has no relation with another relation feature RA (or RB). We used the feature name pairs RA–RAe (or RB–RBe) to make relational similarity between a canonical relation (e.g., the IN relation used in “mountain squirrel”) and its idiosyncratic version (e.g., the INe relation used in “seahorse”) salient.

adjective class. For example, the IN relation binds a noun from a noun class C_1 (e.g., location nouns) and a noun from another noun class C_2 (e.g., animal nouns). C_k indicates a semantic class of nouns but C_5 is a class of adjectives. In this small language, each class consists of two words: $C_k = \{W_1^k, W_2^k\}$. The mapping between a pair of words (N+N or A+N) and a relation is presented in Table 4.3.2. INe and FORe are instantiated in opaque compounds that, in this simulation, were the combinations of the second words of each noun class. In other words, when a noun from C_1 (location) combines with a noun from C_2 (animal), the compound typically instantiates a canonical IN relation but a combination of W_2^1 (e.g., “sea”) and W_2^2 (e.g., “horse”) exceptionally instantiates the INe relation, an idiosyncratic version of the canonical IN relation. Here we assume that the relation participants are disjoint in the sense that a noun that participates in R_i does not participate in R_j for $i \neq j$. This is not strictly plausible relative to natural language (e.g., “mountain magazine” [H-ABOUT-M] and “mountain hut” [H-IN-M], “toy factory” [H-MAKES-M] and “desert factory” [H-IN-M]) but it is roughly true (e.g., “glass,” “rubber,” “summer” as modifier nouns). We adopted this assumption here to make the causes of effects in the model maximally transparent. In the future work, we plan to investigate cases in which the nouns are not so neatly partitioned.

Word meanings were represented in a localist fashion such that a particular word meaning was represented in a particular word meaning unit.

4.3.2 Architecture

The network architecture is presented in Figure 4.3.1. It has 6 relation units at the top layer that represent one of five relations (IN, FOR, INe, FORe, and AN). It has two groups of 12 word meaning units in the middle each of which corresponds to modifier or head; the

TABLE 4.3.2: A toy language used in Simulation 2

Relation	Modifier class	Head class	Compounds or noun phrases
IN	C_1	C_2	$W_1^1 W_1^2, W_1^1 W_2^2, W_2^1 W_1^2$
FOR	C_3	C_4	$W_1^3 W_1^4, W_1^3 W_2^4, W_2^3 W_1^4$
INe	C_1	C_2	$W_2^1 W_2^2$
FORe	C_3	C_4	$W_2^3 W_2^4$
AN	C_5	C_6	$W_1^5 W_1^6, W_1^5 W_2^6, W_2^5 W_1^6, W_2^5 W_2^6$

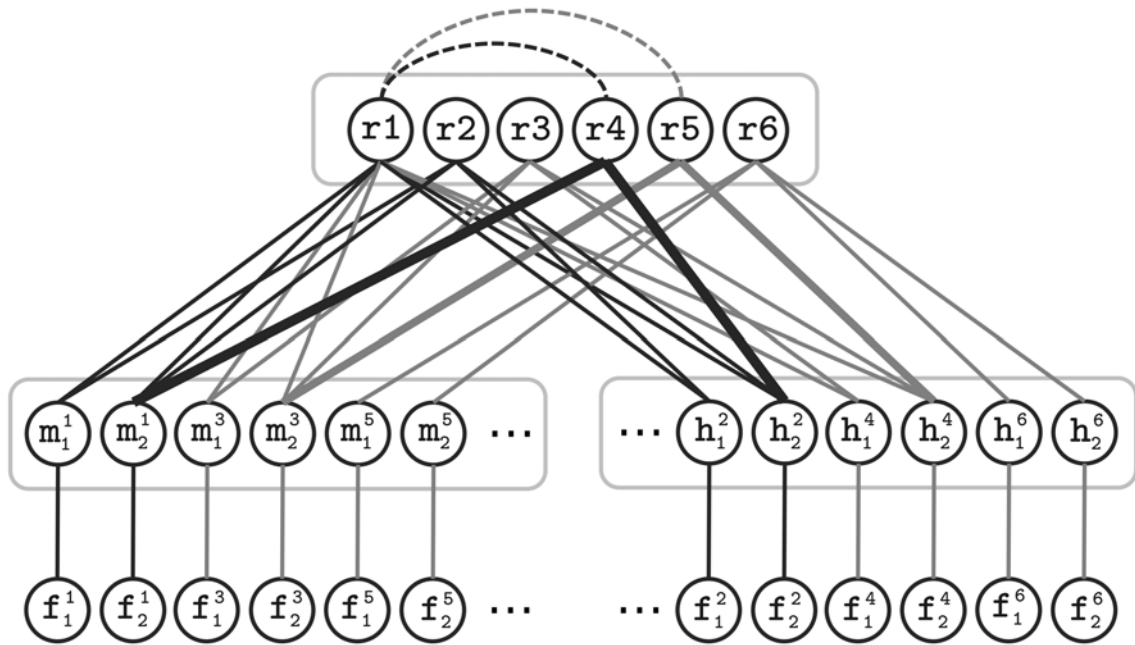


FIGURE 4.3.1: Network architecture. A group of units (r_1, \dots, r_6) at the top layer represents a relation and binds two groups of 12 word meaning units. Only the first 6 units from the modifier group and the second 6 units from the head group are presented in the figure. A unit m_i^j (or h_i^j) represents the meaning of word W_i^j (the i -th word in the j -th class). A unit f_i^j at the bottom represents a word form corresponding to W_i^j . Because word meanings were localist encoded, f_i^j is connected only to m_i^j (on the left) or h_i^j (on the right). Solid lines indicate bottom-up excitatory connections; thicker lines indicate stronger weights. Dashed lines indicate bidirectional inhibitory connections. For example, a combination of class 1 (as modifier) and class 2 (as head) represents either a canonical relation IN (with r_1 and r_2 turned on) or an idiosyncratic relation INe (with r_2 and r_4 turned on) (see the darker lines).

self-organizing treelet model uses two copies of a small word meaning network to represent modifier and head word meaning each. To save space, only half of them are presented in the figure. Only the first 6 units of the modifier group are presented on the left and only the second 6 units of the head group are presented on the right in the figure because six words were used only as modifier and the other six words were used only as head in our simple language. In the figure, solid lines indicate bottom-up excitatory connections and dashed lines indicate bidirectional inhibitory connections; thicker lines indicate stronger weights. Only a small portion of connections is presented in the figure.

First, consider the connections among word meaning units in a small word meaning network, two copies of which are W^{MM} and W^{HH} . Every word meaning unit had a self-excitatory connection and was connected to other word meaning units by inhibitory connections. This pattern of connections made the small network activate only one word meaning unit given a word input; we used a localist representation of word meanings and only one word meaning can be activated given a word input.

Second, consider the connections from word meaning units to relation units. Because we have two copies of the word meaning network, we need to think of two weight matrices: one for the connections from modifier meaning units to relation units (W^{RM}), one for the connections from head meaning units to relation units (W^{RH}). Although the same word meaning network was used to represent modifier and head meanings, the modifier network and the head network can be connected to the relation units differently because a noun as modifier can have a different relation preference from the same noun used as head; in principle, $W^{RM} \neq W^{RH}$. In the current simulation, however, we used the same weights for two groups of connections (modifier to relation and head to relation) because some words were used only as modifier and some words were used only as head.

Third, consider the connections from word form units to word meaning units, W^{MF} (=

W^{HF}). Because we used localist representations of word meanings, m_i^j (or h_i^j) receives the bottom-up support only from f_i^j . Hereafter, we will ignore these connections and focus on the connections between word meaning units and relation units or the connections among relation units.

Figure 4.3.2 presents the weight matrix from modifier meaning units to relation units. The same matrix was used for the connections from head meaning units of head to relation units. Now consider the connection weights from a word meaning unit m_2^1 (e.g., “sea”) to the relation units. Given that a word “sea” (a location noun) participates in the canonical IN relation and the IN relation has two relation features NN and RA, the unit needs to be connected to those two relation units with positive weights. When the word combines with the second noun of the animal class (e.g., “horse”), however, it should activate the idiosyncratic INe relation which has two relation features of RA and RAe. Thus, the same word meaning unit (m_2^1) needs to be connected to those two relation features with positive weights. Once a component noun of an opaque compound can freely combine with other nouns to form transparent compounds instantiating canonical relations, opaque compounds necessarily create an ambiguity among relations which cannot be solved with bottom-up support only. The model can solve the ambiguity problem only by employing inhibitory connections between canonical and idiosyncratic relation features. Note that the excitatory connection from the word meaning unit to an idiosyncratic relation feature RAe has a stronger weight. This is because the model must activate the target idiosyncratic relation features given an opaque compound and win the competition with other canonical relation features. Also opaque words would be more frequent than transparent compounds in natural languages; thus, the stronger connection can be viewed as a sort of compound frequency effect.

The weights of the connections among relation units are presented in Figure 4.3.3. Ev-

ery relation unit has a self-excitatory connection. r_4 (representing a relation feature RAe) and r_5 (representing a relation feature RBe) are connected to r_1 (representing a general relation feature NN) by bidirectional inhibitory connections. As we discussed above, these inhibitory connections are necessary for the model to resolve the ambiguity created by an opaque compound. We assume that the inhibitory connections are learned due to the pressure for the model to treat the ambiguous mapping between word meanings and relations. These bidirectional inter-relation-unit connections implement a (negative) feedback interaction that plays a critical role in predicting the results. In other situations, the network can activate the target relation only using the bottom-up support from word meaning units.⁵ To sum up, the negative connections among some relation units are the result of the need to resolve the ambiguity created by bottom-up support.

Each of word meaning units had a negative bias of -1. Relation units r_1, r_2, r_3 , and r_6 had a negative bias of -1.5 while other relation units r_4 and r_5 had a stronger negative bias of -11. The larger bias was required to activate the idiosyncratic relation features RAe

$$\left(\begin{array}{cccccccccccc} W_1^1 & W_2^1 & W_1^2 & W_2^2 & W_1^3 & W_2^3 & W_1^4 & W_2^4 & W_1^5 & W_2^5 & W_1^6 & W_2^6 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 10 & 0 & 10 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 10 & 0 & 10 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \end{array} \right) \begin{array}{l} \text{NN} \\ \text{RA} \\ \text{RB} \\ \text{RAe} \\ \text{RBe} \\ \text{AN} \end{array}$$

FIGURE 4.3.2: Weights from word meaning units to relation units. w_{ij}^{RM} is a weight of the connection from m_j to r_i for $j \in M, i \in R$. $w^{RH} = w^{RM}$.

⁵In fact, many compounds are ambiguous. A compound can instantiate a canonical relation in a context but another canonical relation in another context. The self-organizing treelet model resolves the ambiguity by activating different word meaning units at the bottom layer; this can be done if the model uses distributed representations of word meanings. Then, a combination of two word meaning vectors can be uniquely connected to a certain relation vector.

and RBe only when those feature units r_4 and r_5 received bottom-up supports from both modifier and head nouns.

4.3.3 Activation dynamics

In Simulation 2, we used the same equations as in Simulation 1 to update the state vectors, y_i^X ($X \in \{R, M, H\}$) (see Section 2.3.2 [p. 36]). As in Simulation 1, the Euler integration with a time constant dt_X was used to approximate continuous state change as follows:

$$y_i^X(t+1) = y_i^X(t) + dt_X \cdot y_i^X(1 - y_i^X)x_i^X \quad (4.3.1)$$

where $dt_R = 0.25$, $dt_M = 2$, $dt_H = 2$; given that word meanings are quickly accessed, a larger time constant was used to model the state change in the modifier and head meaning units. ext_i^X was set to 9.

To avoid problems with roundoff, we set the minimal and maximal activation values to 0.01 and 0.99, respectively.

$$\begin{pmatrix} & \text{NN} & \text{RA} & \text{RB} & \text{RAe} & \text{RBe} & \text{AN} \\ \left(\begin{array}{cccccc} 1 & 0 & 0 & -2 & -2 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ -2 & 0 & 0 & 1 & 0 & 0 \\ -2 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{array} \right) & \begin{array}{l} \text{NN} \\ \text{RA} \\ \text{RB} \\ \text{RAe} \\ \text{RBe} \\ \text{AN} \end{array} \end{pmatrix}$$

FIGURE 4.3.3: Weights from relation units to themselves. w_{ij}^{RR} is a weight from r_j to r_i for $i, j \in R$.

4.3.4 Results

First, we tested whether the model could process all noun phrases (transparent and opaque noun-noun compounds and Adj+N phrases). At the beginning of trials, the initial states of modifier, head, and relation groups were set to a base state at which every unit has a minimal activation value of 0.01. Both constituent words of a test compound or an Adj+N phrase were presented together (as in Experiment 3) to the model. More specifically, an external input was clamped to a modifier meaning unit corresponding to the modifier; another external input was clamped to a head meaning unit corresponding to the head noun. Then, the network updated its modifier, head, and relation states following the equations 2.3.1, 2.3.2, 2.3.3 and 2.3.4. Response time was defined as the number of time steps that the model took until the maximal unitwise error became smaller than 0.1, suggesting every unit was close to its target state at this point. Then the model's response was considered as correct. If the model did not satisfy this response criterion until time step of 150, then we interpreted the model as having failed to understand the compound's meaning. Response times and accuracy for all test cases are presented in Table 4.3.3. The model correctly processed all compounds' meanings.

Once we found the model comprehended noun phrases well, we investigated how the model would behave in a priming situation. We presented a prime phrase first to the model. Before presenting the target phrase, we scaled the end states of the modifier, head, and relation groups by a factor of 0.5, assuming that the activation level of each unit would be reduced after the prime phrase was removed and before the target compound was presented. Then, the target compound was presented to the model. The difference here is that the initial state of the model was set not to the base vector but to the scaled end state after processing a prime phrase. Response time and accuracy were decided as above. We constructed a

TABLE 4.3.3: Response time (timesteps) and accuracy in a simple comprehension task. TR = transparent compounds, OP = opaque compounds, NN = noun-noun compounds, AN = Adj+N phrases.

NP	NP Type	Relation	RT	ACC
$W_1^1 W_1^2$	NN-TR	IN	39	1
$W_1^1 W_2^2$	NN-TR	IN	39	1
$W_2^1 W_1^2$	NN-TR	IN	39	1
$W_2^1 W_2^2$	NN-OP	INe	39	1
$W_1^3 W_1^4$	NN-TR	FOR	39	1
$W_1^3 W_2^4$	NN-TR	FOR	39	1
$W_2^3 W_1^4$	NN-TR	FOR	39	1
$W_2^3 W_2^4$	NN-OP	FORe	39	1
$W_1^5 W_1^6$	AN-TR	AN	39	1
$W_1^5 W_2^6$	AN-TR	AN	39	1
$W_2^5 W_1^6$	AN-TR	AN	39	1
$W_2^5 W_2^6$	AN-TR	AN	39	1

set of prime and target pairs which correspond to prime-target pairs used in Experiment 2 and 3. Table 4.3.4 presents response times (in time steps) and accuracy. Overall, the result patterns resemble the result patterns in Experiment 2 and 3 (see Figure 4.3.4).⁶

First, consider the cases corresponding to three conditions of Experiment 2. The target compound was $W_1^1 W_2^2$ instantiating the IN relation (NN and RA relation features) in all three cases. In the no similarity (NoSim) condition, the prime was $W_1^5 W_1^6$, instantiating the AN relation. Thus, after processing the prime, only the r_6 unit representing the AN feature would be activated. Because there was no interconnection between the AN feature unit and other relation feature units, processing the prime does not influence the target compound comprehension at all. In the low similarity (LoSim) condition, the prime was

⁶In Experiment 3, target compound comprehension was slower when the target was a transparent compound than when the target was an opaque compound. The effect was interpreted as a frequency effect. In Simulation 2, we failed to simulate the main effect of TargetType; actually, target compound comprehension was slower when the target was an opaque word. We suspect that the TargetType effect might change as a function of the relative strengths of the negative bias and the positive bottom-up connections to each idiosyncratic relation unit. This difference is clear in Figure 4.3.5 .

TABLE 4.3.4: Response time (timesteps) and accuracy in a priming experiment. TR = transparent compounds, OP = opaque compounds, NN = noun-noun compounds, AN = Adj+N phrases.

Exp	TargetType	PrimeType	Prime	Target	RT	ACC
2	NN-TR (IN)	NoSim: AN	$W_1^5 W_1^6$	$W_1^1 W_2^2$	39	1
2	NN-TR (IN)	LoSim: FOR	$W_1^3 W_1^4$	$W_1^1 W_2^2$	39	1
2	NN-TR (IN)	HiSim: IN	$W_2^1 W_1^2$	$W_1^1 W_2^2$	25	1
3	NN-OP (INe)	NoSim: AN	$W_1^5 W_1^6$	$W_2^1 W_2^2$	39	1
3	NN-OP (INe)	LoSim: FOR	$W_1^3 W_1^4$	$W_2^1 W_2^2$	57	1
3	NN-OP (INe)	HiSim: IN	$W_1^1 W_1^2$	$W_2^1 W_2^2$	57	1
3	NN-TR (IN)	NoSim: AN	$W_2^5 W_2^6$	$W_1^1 W_1^2$	39	1
3	NN-TR (IN)	LoSim: FORe	$W_2^3 W_2^5$	$W_1^1 W_1^2$	49	1
3	NN-TR (IN)	HiSim: INe	$W_2^1 W_2^2$	$W_1^1 W_1^2$	49	1

$W_1^3 W_1^4$, instantiating the FOR relation. In this case, after processing the prime, two relation units r_1 and r_3 representing NN and RB would be highly activated. Because one of the

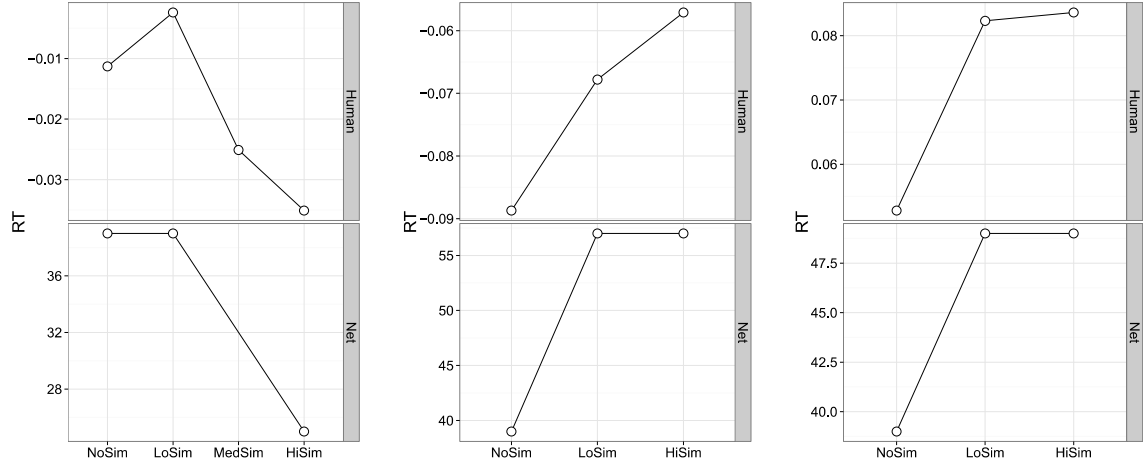


FIGURE 4.3.4: Compound comprehension times (RT) in a priming situation corresponding to (Left) Experiment 2, (Middle) Experiment 3 with opaque compounds as target, or (Right) Experiment 3 with transparent compounds as target. In each subfigure, the top panel shows human participants' data (in residualized times) and the bottom panel shows the model data (in time steps). NoSim = no similarity, LoSim = low similarity, MedSim = medium-level similarity, HiSim = high similarity between prime and target phrases.

target relation features, NN, given the target compound has been already highly activated, the comprehension time for the target compound depends on how quickly the other target relation feature RA is activated. Note that those preactivated units (r_1 and r_3) were not connected to r_2 representing the RA feature. Thus, the state change in r_2 will depend only on the bottom-up support from word meaning units so target compound comprehension in the low similarity condition would be as fast as in the no similarity condition. In the high similarity (HiSim) condition, the prime was $W_2^1 W_1^2$, instantiating the same IN relation. In this case, the target relation features NN and RA given the target compound would be highly activated after processing the prime. Thus, target compound comprehension in the high similarity condition would be faster than in other two conditions.

Second, consider the cases corresponding to three conditions of Experiment 3 in which the target compound was an opaque compound, $W_2^1 W_2^2$, instantiating the INe relation. In the no similarity condition, the prime was $W_1^5 W_1^6$ instantiating the AN relation. As described above, in this case, processing a compound is neither beneficial nor harmful because the r_6

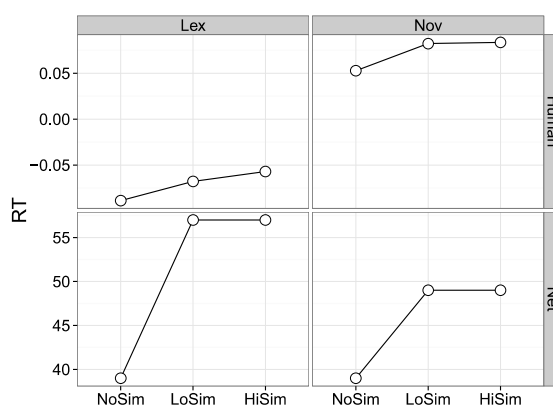


FIGURE 4.3.5: Compound comprehension times (RT) in a priming situation corresponding to Experiment 3. The top panel shows human participants' data (in residualized times) and the bottom panel shows the model data (in time steps). NoSim = no similarity, LoSim = low similarity, MedSim = medium-level similarity, HiSim = high similarity between prime and target phrases. See Footnote 6 (p. 95).

unit was not connected to the target relation feature units r_2 and r_4 . The activation of r_2 and r_4 depends purely on the bottom-up support. In the low similarity condition, two units r_1 and r_3 (representing the FOR relation) are highly activated after processing the prime. Note that the preactivated r_1 unit was connected to the r_4 unit by a bidirectional inhibitory connection. In this case, it will take more time to activate the unit (representing RAe) with the bottom-up support from word meaning units due to its competition with r_1 representing NN. In the high similarity condition, two units r_1 and r_2 (representing the IN relation) after processing the prime. As described, the preactivation of r_1 is harmful for target compound comprehension due to the inhibitory connection between r_1 and r_4 . The preactivation of r_2 representing one of the target relation features RA is not beneficial because the target compound will not be comprehended until the slowly activating r_4 unit is activated highly enough; comprehension time will depend on how quickly r_4 unit is activated. Thus, the rate of target compound comprehension would be comparable in the low and high similarity conditions.

The same thing happens in the other three conditions of Experiment 3 in which the target compound was a transparent compound, $W_1^1 W_1^2$, instantiating the IN relation. Thus, the model processes the target compound slower in the low and high similarity conditions than in the no similarity condition.

4.3.5 Discussion

Simulation 2 gives us an insight about why we observed negative priming in Experiment 3 while we observed positive priming in Experiment 2. The key factor is whether the mapping between a pair of constituent word meanings and a relation is ambiguous. We argued that a unique pair of constituent word meanings is uniquely associated with a par-

ticular canonical relation.⁷ There is no pressure to develop inhibitory connections among canonical relations because a canonical relation can be activated highly only when the relation is supported by both modifier and head. Then, the state change from a canonical relation state to another canonical relation state may happen along a shortest path between two states and travel time will be a function of the between-states distance. Thus, positive priming is expected between two canonical relation states.

On the other hand, the mapping between a pair of constituent word meanings and a relation is necessarily ambiguous. For example, consider an opaque compound “seahorse.” Each of the modifier and head nouns (e.g., “sea” and “horse”) can combine with other nouns from the same semantic class (e.g., “mountain” and “turtle”) to form a transparent compound (e.g., “sea turtle” or “mountain horse”) instantiating a canonical relation (e.g., H-IN-M). Then, a combination of “sea” and “horse” must activate the canonical relation even when the target relation is an idiosyncratic relation. Thus, there is a pressure for a system to develop an inhibitory connection between the canonical relation and its idiosyncratic version, which in turn introduces complex feedback dynamics. Thus, in this case, the state change between a canonical relation and its idiosyncratic version may happen along a curved path between two states; or it might happen along the shortest path but the rate of change might be very slow.

A lesson from Simulation 2 is clear. Processing dynamics is not directly inferred from the spatial organization of the representation space. We must consider feedback dynamics as well to understand processing dynamics underlying online compound comprehension.

⁷We do not argue that a unique pair of word forms is uniquely associated with a particular canonical relation. As proposed in footnote 5 (p. 92), the model can activate different word meanings from a word form input depending on context or other extralinguistic factors.

Chapter 5

General discussion

5.1 Summary

In this study, we proposed a self-organizing treelet model of compound comprehension. According to the model, the comprehension of both transparent and opaque noun-noun compounds requires listeners or readers to build a treelet whose mother node represents a syntactic/semantic relation; the model assumes that syntactic and semantic processing work together to form a particular version of a treelet. The relation space is a similarity space so in a sense the model represents a structure in a similarity space. In addition, there is dynamics on the space which depends on its interaction with the constituents of the input and the timing of their presentation.

In Experiment 1, we investigated if processing difficulty is greater when two constituent nouns prefer different structures (relations) than when two constituent nouns prefer the same structure. According to the CARIN model (Gagné & Shoben, 1997) and other rational models (e.g., Hale, 2006; Levy, 2008), processing difficulty is expected when a modifier

noun strongly prefers a non-target relation because it misleads a language processing system to adopt a wrong interpretation. However, based on the self-organizing treelet model and other prior studies on local coherence effects (Tabor et al., 2004), we predicted compound comprehension would be disturbed if the head noun prefers a non-target relation even when the modifier noun prefers a target relation. We found both garden path and local coherence effects, rejecting the CARIN and other rational models. The exemplar model proposed by Devereux and Costello (2006) cannot explain the local coherence effect either because the model, without feedback dynamics, predicts processing difficulty based on the distance (or similarity) between the relation state after processing a modifier noun and the relation state after processing a head noun. In the local coherence condition, after processing the modifier noun, the exemplar model predicts that the relation state is close to the target relation state. Thus, compound comprehension must not be difficult in the local coherence case. Note that both effects are observed in the same construction, suggesting that two effects are not qualitatively different but stem from the tension between one interpretation and the other interpretation which seems to be graded.

To investigate the organization of the relation space, first we ran a free card sorting task. The analysis of card sorting data revealed three important properties of the relation space. First, perceived relational similarity is graded. Second, compound relations formed a small number of clouds in the relation space each of which corresponds to a particular relation class. Third, multiple subgroups of compounds could be distinguished within a more general relation class, suggesting the hierarchical organization of relations. A continuous relation space hypothesis (Devereux & Costello, 2006) provides a comprehensive account of all three properties.

In Experiment 2, we tested if the comprehension of a transparent compound instantiating a relation can be facilitated after processing another compound instantiating a similar

relation. According to Estes and Jones (2006), the graded positive priming is expected. We introduced graded relational similarity by choosing target compounds that instantiate certain relations that were proposed to have subclasses. Then, four conditions were constructed such that the prime was an Adj + N phrase (no structural similarity), noun-noun compounds instantiating a different relation from the target compound (low structural similarity), noun-noun compounds instantiating the same general relation but a different subclass (medium-level structural similarity), and noun-noun compounds that instantiate very similar relations (high structural similarity). We observed the contrast between the first two conditions and the last two conditions. We rejected a simple syntactic priming account because we did not observe any reading time difference between the first two conditions. Although we replicated relation priming in sentence reading, we failed to provide evidence for graded structural parallelism effect.

Inspired by a connectionist approach to inflectional morphology, we proposed a single mechanism view of compound processing and representation; we argued that opaque compounds are represented in the continuous relation space and processed by the same mechanism as transparent compounds are. If transparent and opaque compounds share the relation space, a processing of one kind will influence the processing of the other. Three models were considered. First, the words-and-rules theory predicts negative priming between transparent and opaque compounds as well as between any idiosyncratic expressions and any compositional expressions because the competition happens between two mechanisms, not just two expressions. Second, we argued that the spatial models like Devereux and Costello (2006) could employ any kind of nonlinear function between distance in the representation space and processing difficulty measured by response times. However, we pointed out that once the function is chosen, the same function should be used. Thus, the model predicts positive priming between transparent and opaque compounds because pos-

itive priming between transparent compounds instantiating similar relations was observed in Experiment 2.

Experiment 2 and 3 together suggests that priming cannot be explained just by investigating structural similarity in the relation space. Instead, we need to consider feedback dynamics on the representation space. Based on our simulation work, we argued that negative priming is due to competition between canonical and idiosyncratic relations that was originated from the ambiguity in a mapping between constituent meaning and relations created by compositional processing.

5.2 Implications

Although this study focused on a simple linguistic construction, noun-noun compounds, the main idea can extend to all kinds of constituent structures because a relation can have another constituent structure as its argument. In terms of representation, a main message is that a binding node of a treelet has its own relational meaning which is represented as a vector in a continuous, hierarchically organized, similarity metric space (see Chapter 3, Free Card Sorting Task). As assumed when we used A + N phrases as prime in the no similarity condition in Experiment 2 and 3, every syntactic structure has its own relational meaning. For example, the relational vectors associated with different syntactic relations (e.g., A + N vs. N + N) are located far from each other. Some relation classes (e.g., N+N) have multiple subclasses. Within every class of relations, our model predicts that there is a gradation of relational meanings such that some relational meanings are more typical than others.

When we consider the whole relation space (or the space of all possible syntactic struc-

tures), the similarity relationship among those relational meanings will not be clear because perceived similarity decays exponentially as the distance between two relations increases (Shepard, 1987).

Another important argument in our study is that apparently less compositional meanings of some combinations of nouns (e.g., “snowman,” “seahorse”) are represented in the same relation space as compositional combinations of nouns (e.g., “paper cup”) and processed by a single mechanism. Similar suggestions have been proposed to explain the quasi-regular patterns (i.e., rule-like patterns plus exceptions) observed in orthography-phonology mapping (Harm & Seidenberg, 2004; Plaut et al., 1996; Seidenberg & McClelland, 1989), inflectional morphology (Hare, Elman, & Daugherty, 1995; McClelland & Patterson, 2002a; Tabor, Cho, & Szkudlarek, 2013) and derivational morphology (Seidenberg & Gonnerman, 2000), compounding (Haskell, MacDonald, & Seidenberg, 2003), phrasal verbs and idioms (Cacciari & Tabossi, 1988; Cutting & Bock, 1997). Also relevant is the argument for compositionality on a continuum in lexicalized noun-noun compounds (Libben, 1998; Reddy et al., 2011) and phrasal verbs (McCarthy, Keller, & Carroll, 2003).

However, the vector representation of syntactic/semantic structures is one aspect of our model. In our experiments, we showed that feedback dynamics should be considered to understand online comprehension. Vector-based (probabilistic) models (e.g., Devereux & Costello, 2006) tend to explain processing difficulty associated with a transition from one state to another state based on the distance between two states. However, Experiment 3 suggests that the hypothesis is too simple to capture a complex relationship between distance and processing difficulty. Dynamical aspects of the relation space should be considered. As we argued in the discussion of Experiment 1, the same argument can be applied to probabilistic models of sentence processing which tends to associate processing difficulty with a distance between a probability (density) distribution before a word input and another

distribution after the word input (Hale, 2006; Levy, 2008). In Simulation 2, we proposed a hypothesis that such complex dynamics is developed for a language system to cope with the ambiguity present in the mapping from constituent nouns to relations. Note that either component noun of an opaque compound can combine with other nouns to participate in other relations/structures that possibly compete with the target idiosyncratic relation. To prevent the competition, a language processing system cannot develop inhibitory connections from either constituent noun to other compositional relations because in this case, the system cannot use the constituent noun as a building block of transparent compounds any more. The only way to handle the situation is to develop strong inhibitory relations between the relation and other canonical, compositional relations. This is true even when compositional and non-compositional relations are somehow relationally similar (e.g., “seahorse” and “field mouse”). There exists such competition between canonical, compositional relations as we observed in Experiment 1. But in this case, competition is developed only between highly different relations that cannot coexist.

An interesting case to which our model can be applied is enriched composition (Jackendoff, 1997) which refers to apparently simple constructions that require complex semantic composition. Examples are “The author began the book” (Pustejovsky, 1996) and “difficult mountain” (Frisson, Pickering, & McElree, 2011). The second example is particularly interesting due to the combination of its simplicity in syntax and its complexity in semantics that makes noun-noun compounds an interesting topic. It is interesting if our model can handle such cases.

5.3 Future directions

In this section, we propose future plans to extend this study in several different ways.

5.3.1 Representation and processing dynamics of noun-noun-noun compounds

Noun-noun compounding is recursive in English (Selkirk, 1982) and many other languages. Some examples are noun-noun-noun compounds like “woman aid worker” ([woman [aid worker]]) and “hydrogen ion exchange” ([[hydrogen ion] exchange]) (Lauer, 1995a). Some examples are ambiguous as in “backup compiler disk” ([backup [compiler disk]] or [[backup compiler] disk]) (Lauer, 1995a). This more complex pattern $N_1 N_2 N_3$ introduces another kind of structural ambiguity between $[N_1 [N_2 N_3]]$ and $[[N_1 N_2] N_3]$. The same kind of ambiguity is observed in the interpretation of a construction $PP PP PP$ as either $[PP [PP PP]]$ or $[[PP PP] PP]$ (e.g., “influence of the temperature on the electrons in Fahrenheit” [Wermter & Lehnert, 1992]). But compound cases are more difficult because a particular relation needs to be specified for each binding node. Figure 5.3.1 presents two sets of possible interpretations in which R_i and R_j (or R_k and R_l) need to be specified during comprehension.

Prior researchers have mainly focused on the end product of compound interpretation (e.g., Girju et al., 2005; Lauer, 1995a). Our interest is in a dynamical process by which a



FIGURE 5.3.1: Two sets of possible interpretations of $N_1 N_2 N_3$

system solves the structural ambiguity in online comprehension. To study it, we propose a new relation priming paradigm. In this paradigm, a three-noun compound $N_1 N_2 N_3$ (instantiating R_i and R_j , or R_k and R_l ; see Figure 5.3.1) is presented in a sentence frame (as we did in this study) visually or auditorily such that the component nouns are processed sequentially. A noun-noun or noun-noun-non combination is presented suddenly at a certain time point while participants are reading the sentence. The time point is one of the following positions: before N_1 , after N_1 , after N_2 , after N_3 , or 500 ms after N_3 . Participants are asked to judge if the test combination is sensible. Two types of combinations can be used as test stimulus. A noun-noun compound instantiating a relation R_i or R_j combinations can be used to investigate the time course of the activation of the simple relation during the comprehension of the NNN compound. NNN combinations can be used to investigate the effect of structural parallelism in a global structure (complex relation). For example, participants might respond to the test combination typically interpreted as the left of Figure 5.3.1 faster after reading/listening to the NNN compounds interpreted similarly than after reading/listening to the NNN compounds interpreted as the right of Figure 5.3.1. A series of experiments are planned to investigate this complex dynamics involved in this kind of ambiguity resolution. Closely related to the above question, we have a plan to run the garden path and local coherence effects in noun-noun-noun compounds as we did in Experiment 1.

Another research question is about the semantic/structural patterns of NNN compounds. Specifically, we ask if there is a specific relation ordering (like adjective ordering) such that when two relations R_1 and R_2 are combined, R_1 is placed higher than R_2 , like $[R_1 N_1 [R_2 N_2 N_3]]$ or $[R_1 [R_2 N_1 N_2] N_3]$ but not like $[R_2 N_1 [R_1 N_2 N_3]]$ or $[R_2 [R_1 N_1 N_2] N_3]$.

Almost all languages are recursive (Chomsky, 1957; Hauser, Chomsky, & Fitch, 2002; but see Everett, 2005). An important question is how a language processing system repre-

sents the recursive structure. This question has been extensively studied and many elegant proposals have been made (Elman, 1991; Plate, 1995; Pollack, 1990; Smolensky, 1990; Tabor, 2000). What we need more is the discussion of feedback dynamics in online processing. In this study, we chose two-noun compounds because they are minimal expressions in which complex feedback dynamics can be studied. Three-noun compounds, we argue, are minimal expressions in which the role of complex feedback dynamics in recursive structure building can be studied thoroughly.

5.3.2 Structure of the relation space

In this study, we argued for the hierarchical organization of the relation space (see also Devereux & Costello, 2005). Our argument was based on the data collected from a small number of participants. We consider a large scale study of the relation space, with more compounds and more participants.

Recall that we observed the clear separation among 5 relation classes. Each relation class seems to be equally dissimilar to each of the other relation classes. This might be due to that perceived similarity between two relations decreases quickly as the distance between two relations in the relation space increases. Card sorting of very different relations might not detect gradedness of relation similarity (in terms of between-relations distance in the representation space). Taxonomic free card sorting (Courcoux, Qannari, Taylor, Buck, & Greenhoff, 2012) can be used to get graded similarity scores. In taxonomic card sorting, participants perform a free card sorting task first. Once they finish the task, they are asked to choose two groups of cards that they think are most similar and collapse them to form a new group. In other words, they are forced to combine two groups of cards based on group-level similarity again and again. This process is iterated until they form one big pile

of cards.¹ If class-level relational similarity is similar for every pair of relation classes, different participants will collapse the piles of cards in different orders. On the other hand, if participants collapse the card piles in similar orders, it suggests that class-level relational similarity is graded. We propose a taxonomic card sorting task as a way of investigating the global organization of the relation space.

5.3.3 Learning neural network models

In Simulation 1, we used a learning recurrent neural network model with random vectors. For the simulation of Experiment 1, we did not require any detailed distribution of relation vectors. It was enough to use localist representations of relation states and create random vectors such that two groups of relation vectors can be separated easily.

We used a hand-coded model in Simulation 2. To simulate Experiment 2 and 3, it was necessary to use distributed representation of relations and moreover have particularly structured sets of relations. However, the model would be hard to understand. Thus, under the assumption that (1) relations are hierarchically organized and (2) inhibitory connections should be developed between competing relation features to solve ambiguity, we constructed the target relation states and the connection weights by hand. The next step is to build a learning model and test if the learning model develops the weights such that the model's dynamics is similar to our model in Simulation 2. For this purpose, it should be considered how the target conceptual and relational feature vectors can be acquired.

Conceptual feature vectors could be acquired from a semantic feature production task. In a norming study, Cree and McRae (2003) gave 20 or 24 concrete names (e.g., “cat”) and asked participants to list up to 10 features of what the name refers to. Once participants

¹The procedure resembles the way how agglomerative hierarchical clustering algorithm works.

generated the features for each concept, a concept can be represented as a vector of feature frequencies. After normalizing the feature vectors, they can be directly used as the target concept states. Cree and McRae (2003) showed that the norming data revealed the hierarchical organization of conceptual space. The method is less noisy but limited to concepts whose semantic features are easy to verbalize.

Another way to get the conceptual feature vectors is to use corpus-based models like the Hyperspace Analogue to Language (HAL) (Lund & Burgess, 1996), the Latent Semantic Analysis (LSA) (Landauer & Dumais, 1997), the Bound Encoding of the Aggregate Language Environment (BEAGLE) model (Jones & Mewhort, 2007), the TOPICS model (Griffiths, Steyvers, & Tenenbaum, 2007), and so on.

Target relation vectors can be acquired from running a relation selection task (Devereux & Costello, 2006) in which participants were asked to choose any number of relations from a relation list that can paraphrase the presented compound. We argued that the task might not be ideal because relational similarity between two relations that are different in terms of constituent order (e.g., H-CAUSES-M, H-CAUSED-BY-M) will be underestimated because participants can clearly see the distinction from the screen. However, the task is easy to implement and allows researchers to collect data quickly. Depending on what relations are of research interest, this task will be appropriate for the purpose of getting the target relation state. This method seems to be appropriate when the research focus is on the global structure of the relation space.

(Taxonomic) free card sorting task is an alternative way to construct the relation space. We applied multidimensional scaling to similarity data to get a vector for each compound. The relation vectors can be used as target relation vectors for the compounds.

One important aspect that we can learn from the learning self-organizing treelet model with the training corpus with rich semantics is the developmental change of the relation

space which introduces the change in feedback dynamics in a fast time scale. Also the study of the learning models will provide us to chance possibly progressive destruction of the representation system, for example, as in semantic dementia patients (McClelland & Rogers, 2003).

5.4 Conclusion

Noun-noun compounds have word-like properties and sentence-like properties so provide a chance to study various questions that have been studied separately. While garden path and local coherence effects have been studied using different linguistic constructions in the sentence processing literature, in Experiment 1, we investigated those effects using the same construction, noun-noun compounds, requiring syntactic and semantic processing, unlike the studies of both effects in spoken word recognition (Allopenna, Magnuson, & Tanenhaus, 1998; Magnuson, Tanenhaus, Aslin, & Dahan, 2003). In Experiments 2 and 3, we used compounds to study the effect of structural parallelism with the assumption of a spatial encoding of structure. We observed the opposite effects, positive priming between transparent compounds in Experiment 2 and negative priming between transparent and opaque compounds in Experiment 3, which clearly reveals that simple similarity-based dynamics is not enough. All three experiments together reveal the importance of feedback dynamics combined with the spatial encoding of meaning. Much efforts should be given to the study of the interaction between the representation and feedback dynamics, which will give us better understanding of language processing.

Appendix A

Materials used in Experiment 1

Materials used in Experiment 1 are presented in the table below. In the table, BL, LC, and GP indicate the baseline, local coherence, and garden path conditions, respectively; F indicates nonsense noun-noun combinations. AR indicates the average acceptance rate in the sensibility judgment task.

ID	Cond	Compound	AR	ID	Cond	Compound	AR
1	BL	math magazine	0.974	101	F	air lakes	0.105
2	LC	paper magazine	1.000	102	F	book tension	0.605
3	GP	mountain magazine	0.974	103	F	vegetable pains	0.026
4	BL	voice commercial	0.868	104	F	wreath nerves	0.026
5	LC	morning commercial	0.921	105	F	milk shape	0.289
6	GP	song commercial	0.842	106	F	bleach mustache	0.526
7	BL	physics homework	1.000	107	F	cable underwear	0.079
8	LC	April homework	0.842	108	F	moth range	0.263
9	GP	insect homework	0.868	109	F	manual mat	0.184
10	BL	fatigue headache	0.868	110	F	sap toy	0.316
11	LC	midnight headache	0.868	111	F	attic leg	0.079
12	GP	rubber headache	0.026	112	F	honey range	0.368

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ID	Cond	Compound	AR	ID	Cond	Compound	AR
13	BL	oil money	0.816	113	F	cactus hormone	0.632
14	LC	metal money	0.684	114	F	gasoline mercy	0.000
15	GP	alumni money	0.921	115	F	electronic curry	0.053
16	BL	baby doctor	0.974	116	F	cane tale	0.368
17	LC	woman doctor	1.000	117	F	sweater breeze	0.026
18	GP	chair doctor	0.158	118	F	warrior cloud	0.263
19	BL	jewel store	1.000	119	F	treatment hole	0.474
20	LC	airport store	0.974	120	F	olive signals	0.079
21	GP	basket store	1.000	121	F	pine rains	0.158
22	BL	widget factory	0.816	122	F	cream property	0.053
23	LC	country factory	0.737	123	F	flour rug	0.053
24	GP	foam factory	0.974	124	F	steam thorn	0.026
25	BL	spleen disease	0.947	125	F	finger tree	0.132
26	LC	fertility disease	0.974	126	F	picture soup	0.000
27	GP	cucumber disease	0.763	127	F	frog cub	0.132
28	BL	island bird	1.000	128	F	fish cow	0.026
29	LC	winter bird	0.974	129	F	lemon hormone	0.500
30	GP	landfill bird	0.579	130	F	snow betrayal	0.132
31	BL	union lawyer	0.947	131	F	fruit nerves	0.105
32	LC	lifetime lawyer	0.684	132	F	rain glands	0.105
33	GP	pope lawyer	0.395	133	F	liquor keyboard	0.026
34	BL	travel album	0.947	134	F	pudding lamp	0.026
35	LC	leather album	0.842	135	F	salivary cube	0.105
36	GP	school album	0.974	136	F	spinal wine	0.000
37	BL	ion cloud	0.816	137	F	gutter season	0.342
38	LC	ocean cloud	0.342	138	F	sap peel	0.237
39	GP	mosquito cloud	0.737	139	F	vacuum butter	0.000
40	BL	rescue equipment	0.974	140	F	copper friendship	0.026
41	LC	company equipment	0.974	141	F	tuition stove	0.000
42	GP	sand equipment	0.974	142	F	daisy force	0.184
43	BL	juice bowl	0.921	143	F	heat cow	0.079
44	LC	table bowl	0.500	144	F	shock members	0.500
45	GP	cranberry bowl	0.974	145	F	dependence apple	0.000

Appendix B

Materials used in Experiment 2

Materials used in Experiment 2 are presented in the table below. Structural/relational similarity between prime and target compounds (PrimeType) was manipulated across four levels. In the table, NoSim, LoSim, MedSim, and HiSim indicate the no similarity, low similarity, medium-level similarity, and high similarity conditions, respectively. PrimeRel and TargRel indicate the relations that prime and target compounds instantiate. We emphasize, however, that regarding our research question, what matters is not the specific classification of compounds into relation classes but the relational similarity between prime and target compounds.

SetID	PrimeType	Prime	PrimeRel	Target	TargRel
1	NoSim	dangerous pills	ADJ	cough medicines	FOR2
1	LoSim	herb pills	MADE-OF	cough medicines	FOR2
1	MedSim	fertility pills	FOR1	cough medicines	FOR2
1	HiSim	allergy pills	FOR2	cough medicines	FOR2
2	NoSim	strong sprays	ADJ	rest chairs	FOR1
2	LoSim	aerosol sprays	HAVE1	rest chairs	FOR1

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SetID	PrimeType	Prime	PrimeRel	Target	TargRel
2	MedSim	bug sprays	FOR2	rest chairs	FOR1
2	HiSim	pet sprays	FOR1	rest chairs	FOR1
3	NoSim	plain pants	ADJ	lightning rods	FOR2
3	LoSim	leather pants	MADE-OF	lightning rods	FOR2
3	MedSim	heat pants	FOR1	lightning rods	FOR2
3	HiSim	water pants	FOR2	lightning rods	FOR2
4	NoSim	popular shampoos	ADJ	security lenses	FOR1
4	LoSim	vitamin shampoos	HAVE1	security lenses	FOR1
4	MedSim	dandruff shampoos	FOR2	security lenses	FOR1
4	HiSim	moisture shampoos	FOR1	security lenses	FOR1
5	NoSim	cute shoes	ADJ	dust goggles	FOR2
5	LoSim	rubber shoes	MADE-OF	dust goggles	FOR2
5	MedSim	fitness shoes	FOR1	dust goggles	FOR2
5	HiSim	rain shoes	FOR2	dust goggles	FOR2
6	NoSim	cheap jackets	ADJ	study lamps	FOR1
6	LoSim	wool jackets	MADE-OF	study lamps	FOR1
6	MedSim	wind jackets	FOR2	study lamps	FOR1
6	HiSim	sweat jackets	FOR1	study lamps	FOR1
7	NoSim	daunting walls	ADJ	sun umbrellas	FOR2
7	LoSim	stone walls	MADE-OF	sun umbrellas	FOR2
7	MedSim	safety walls	FOR1	sun umbrellas	FOR2
7	HiSim	noise walls	FOR2	sun umbrellas	FOR2
8	NoSim	unfair laws	ADJ	stamina foods	FOR1
8	LoSim	finance laws	ABOUT	stamina foods	FOR1
8	MedSim	torture laws	FOR2	stamina foods	FOR1
8	HiSim	copyright laws	FOR1	stamina foods	FOR1
9	NoSim	solid fences	ADJ	mud boots	FOR2
9	LoSim	iron fences	MADE-OF	mud boots	FOR2
9	MedSim	baby fences	FOR1	mud boots	FOR2
9	HiSim	burglar fences	FOR2	mud boots	FOR2
10	NoSim	favorite lotions	ADJ	health diets	FOR1
10	LoSim	citrus lotions	MADE-OF	health diets	FOR1
10	MedSim	wrinkle lotions	FOR2	health diets	FOR1
10	HiSim	hair lotions	FOR1	health diets	FOR1

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SetID	PrimeType	Prime	PrimeRel	Target	TargRel
11	NoSim	recent wars	ADJ	measles vaccines	FOR2
11	LoSim	Iraq wars	IN1	measles vaccines	FOR2
11	MedSim	freedom wars	FOR1	measles vaccines	FOR2
11	HiSim	pest poisons	FOR2	measles vaccines	FOR2
12	NoSim	illegal drugs	ADJ	horse doctors	FOR1
12	LoSim	protein drugs	HAVE1	horse doctors	FOR1
12	MedSim	cancer drugs	FOR2	horse doctors	FOR1
12	HiSim	heart drugs	FOR1	horse doctors	FOR1
13	NoSim	silent prayers	ADJ	street riots	IN1
13	LoSim	money prayers	FOR1	street riots	IN1
13	MedSim	sunset prayers	IN2	street riots	IN1
13	HiSim	cave prayers	IN1	street riots	IN1
14	NoSim	boring life	ADJ	summer safaris	IN2
14	LoSim	party life	HAVE1	summer safaris	IN2
14	MedSim	island life	IN1	summer safaris	IN2
14	HiSim	weekday life	IN2	summer safaris	IN2
15	NoSim	dark clouds	ADJ	wilderness roads	IN1
15	LoSim	plasma clouds	MADE-OF	wilderness roads	IN1
15	MedSim	morning clouds	IN2	wilderness roads	IN1
15	HiSim	ocean clouds	IN1	wilderness roads	IN1
16	NoSim	exciting sports	ADJ	midnight trains	IN2
16	LoSim	ball sports	USE	midnight trains	IN2
16	MedSim	river sports	IN1	midnight trains	IN2
16	HiSim	summer sports	IN2	midnight trains	IN2
17	NoSim	bumpy trails	ADJ	seaside bungalows	IN1
17	LoSim	bicycle trails	FOR	seaside bungalows	IN1
17	MedSim	autumn trails	IN2	seaside bungalows	IN1
17	HiSim	hill trails	IN1	seaside bungalows	IN1
18	NoSim	shabby lodges	ADJ	March sales	IN2
18	LoSim	oak lodges	MADE-OF	March sales	IN2
18	MedSim	mountain lodges	IN1	March sales	IN2
18	HiSim	weekend lodges	IN2	March sales	IN2
19	NoSim	fierce battles	ADJ	attic floors	IN1
19	LoSim	death battles	CAUSE1	attic floors	IN1

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SetID	PrimeType	Prime	PrimeRel	Target	TargRel
19	MedSim	night battles	IN2	attic floors	IN1
19	HiSim	sea battles	IN1	attic floors	IN1
20	NoSim	arduous journeys	ADJ	winter storms	IN2
20	LoSim	ferry journeys	USE	winter storms	IN2
20	MedSim	space journeys	IN1	winter storms	IN2
20	HiSim	evening journeys	IN2	winter storms	IN2
21	NoSim	expensive parties	ADJ	desert lizards	IN1
21	LoSim	book parties	FOR	desert lizards	IN1
21	MedSim	spring parties	IN2	desert lizards	IN1
21	HiSim	beach parties	IN1	desert lizards	IN1
22	NoSim	difficult adventures	ADJ	childhood dreams	IN2
22	LoSim	boat adventures	USE	childhood dreams	IN2
22	MedSim	prairie adventures	IN1	childhood dreams	IN2
22	HiSim	college adventures	IN2	childhood dreams	IN2
23	NoSim	remarkable achievements	ADJ	office friendships	IN1
23	LoSim	pupil achievements	NOM	office friendships	IN1
23	MedSim	lifetime achievements	IN2	office friendships	IN1
23	HiSim	school achievements	IN1	office friendships	IN1
24	NoSim	tremendous turmoils	ADJ	Thanksgiving guests	IN2
24	LoSim	explosion turmoils	CAUSE2	Thanksgiving guests	IN2
24	MedSim	ghetto turmoils	IN1	Thanksgiving guests	IN2
24	HiSim	adolescence turmoils	IN2	Thanksgiving guests	IN2
25	NoSim	terrible pains	ADJ	accident carelessness	CAUSE1
25	LoSim	ankle pains	IN1	accident carelessness	CAUSE1
25	MedSim	birth pains	CAUSE2	accident carelessness	CAUSE1
25	HiSim	infection germs	CAUSE1	accident carelessness	CAUSE1
26	NoSim	fatal viruses	ADJ	laugh hiccups	CAUSE2
26	LoSim	dog viruses	IN1	laugh hiccups	CAUSE2
26	MedSim	flu viruses	CAUSE1	laugh hiccups	CAUSE2
26	HiSim	coffee nerves	CAUSE2	laugh hiccups	CAUSE2
27	NoSim	tiny holes	ADJ	tear gases	CAUSE1
27	LoSim	ice holes	IN1	tear gases	CAUSE1
27	MedSim	moth holes	CAUSE2	tear gases	CAUSE1
27	HiSim	malaria mosquitoes	CAUSE1	tear gases	CAUSE1

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SetID	PrimeType	Prime	PrimeRel	Target	TargRel
28	NoSim	scary stories	ADJ	snow blindness	CAUSE2
28	LoSim	wolf stories	ABOUT	snow blindness	CAUSE2
28	MedSim	sob stories	CAUSE1	snow blindness	CAUSE2
28	HiSim	onion tears	CAUSE2	snow blindness	CAUSE2
29	NoSim	painful scars	ADJ	growth hormones	CAUSE1
29	LoSim	hand scars	IN1	growth hormones	CAUSE1
29	MedSim	bullet scars	CAUSE2	growth hormones	CAUSE1
29	HiSim	cancer genes	CAUSE1	growth hormones	CAUSE1
30	NoSim	worrisome situations	ADJ	cocaine deaths	CAUSE2
30	LoSim	outside situations	IN1	cocaine deaths	CAUSE2
30	MedSim	anxiety situations	CAUSE1	cocaine deaths	CAUSE2
30	HiSim	vapor locks	CAUSE2	cocaine deaths	CAUSE2
31	NoSim	unbearable tensions	ADJ	trauma events	CAUSE1
31	LoSim	classroom tensions	IN1	trauma events	CAUSE1
31	MedSim	job tensions	CAUSE2	trauma events	CAUSE1
31	HiSim	suspense films	CAUSE1	trauma events	CAUSE1
32	NoSim	emotional movies	ADJ	fatigue headaches	CAUSE2
32	LoSim	superhero movies	ABOUT	fatigue headaches	CAUSE2
32	MedSim	horror movies	CAUSE1	fatigue headaches	CAUSE2
32	HiSim	cold cracks	CAUSE2	fatigue headaches	CAUSE2
33	NoSim	recurrent diseases	ADJ	suicide bombings	CAUSE1
33	LoSim	brain diseases	IN1	suicide bombings	CAUSE1
33	MedSim	deficiency diseases	CAUSE2	suicide bombings	CAUSE1
33	HiSim	risk behaviors	CAUSE1	suicide bombings	CAUSE1
34	NoSim	imminent decisions	ADJ	separation anxieties	CAUSE2
34	LoSim	court decisions	IN1	separation anxieties	CAUSE2
34	MedSim	investment decisions	CAUSE1	separation anxieties	CAUSE2
34	HiSim	investment benefits	CAUSE2	separation anxieties	CAUSE2
35	NoSim	severe fires	ADJ	surprise attacks	CAUSE1
35	LoSim	church fires	IN1	surprise attacks	CAUSE1
35	MedSim	cigarette fires	CAUSE2	surprise attacks	CAUSE1
35	HiSim	red-card fouls	CAUSE1	surprise attacks	CAUSE1
36	NoSim	official actions	ADJ	wind burns	CAUSE2
36	LoSim	courtroom actions	IN1	wind burns	CAUSE2

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SetID	PrimeType	Prime	PrimeRel	Target	TargRel
36	MedSim	enforcement actions	CAUSE1	wind burns	CAUSE2
36	HiSim	juice stains	CAUSE2	wind burns	CAUSE2
37	NoSim	narrow doors	ADJ	lace handkerchiefs	HAVE1
37	LoSim	glass doors	MADE-OF	lace handkerchiefs	HAVE1
37	MedSim	kitchen doors	HAVE2	lace handkerchiefs	HAVE1
37	HiSim	peephole doors	HAVE1	lace handkerchiefs	HAVE1
38	NoSim	steep roofs	ADJ	melon peels	HAVE2
38	LoSim	straw roofs	MADE-OF	melon peels	HAVE2
38	MedSim	chimney roofs	HAVE1	melon peels	HAVE2
38	HiSim	building roofs	HAVE2	melon peels	HAVE2
39	NoSim	dense forests	ADJ	spa resorts	HAVE1
39	LoSim	highland forests	IN1	spa resorts	HAVE1
39	MedSim	government forests	HAVE2	spa resorts	HAVE1
39	HiSim	swamp forests	HAVE1	spa resorts	HAVE1
40	NoSim	warm houses	ADJ	tire rims	HAVE2
40	LoSim	vacation houses	FOR1	tire rims	HAVE2
40	MedSim	pool houses	HAVE1	tire rims	HAVE2
40	HiSim	shirt collars	HAVE2	tire rims	HAVE2
41	NoSim	long halls	ADJ	dolphin aquariums	HAVE1
41	LoSim	entrance halls	IN1	dolphin aquariums	HAVE1
41	MedSim	castle halls	HAVE2	dolphin aquariums	HAVE1
41	HiSim	statue halls	HAVE1	dolphin aquariums	HAVE1
42	NoSim	shady groves	ADJ	company assets	HAVE2
42	LoSim	evening groves	IN2	company assets	HAVE2
42	MedSim	orange groves	HAVE1	company assets	HAVE2
42	HiSim	university groves	HAVE2	company assets	HAVE2
43	NoSim	famous stores	ADJ	fruit baskets	HAVE1
43	LoSim	airport stores	IN1	fruit baskets	HAVE1
43	MedSim	company stores	HAVE2	fruit baskets	HAVE1
43	HiSim	coat stores	HAVE1	fruit baskets	HAVE1
44	NoSim	empty bottles	ADJ	fish scales	HAVE2
44	LoSim	copper bottles	MADE-OF	fish scales	HAVE2
44	MedSim	potion bottles	HAVE1	fish scales	HAVE2
44	HiSim	tree trunks	HAVE2	fish scales	HAVE2

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SetID	PrimeType	Prime	PrimeRel	Target	TargRel
45	NoSim	fertile lands	ADJ	walnut cakes	HAVE1
45	LoSim	hunting lands	FOR	walnut cakes	HAVE1
45	MedSim	county lands	HAVE2	walnut cakes	HAVE1
45	HiSim	reindeer lands	HAVE1	walnut cakes	HAVE1
46	NoSim	thick books	ADJ	family antiques	HAVE2
46	LoSim	kid books	FOR1	family antiques	HAVE2
46	MedSim	picture books	HAVE1	family antiques	HAVE2
46	HiSim	library books	HAVE2	family antiques	HAVE2
47	NoSim	clean rooms	ADJ	flower gardens	HAVE1
47	LoSim	bachelor rooms	FOR1	flower gardens	HAVE1
47	MedSim	hotel rooms	HAVE2	flower gardens	HAVE1
47	HiSim	bar rooms	HAVE1	flower gardens	HAVE1
48	NoSim	delicious soups	ADJ	tractor engines	HAVE2
48	LoSim	stamina soups	FOR1	tractor engines	HAVE2
48	MedSim	vegetable soups	HAVE1	tractor engines	HAVE2
48	HiSim	apple cores	HAVE2	tractor engines	HAVE2

Appendix C

Materials used in Experiment 3

Materials used in Experiment 3 are presented in the table below. The target compound type (TargetType) was manipulated across two levels (Opaque vs. Transparent). Structural/relational similarity between prime and target compounds (PrimeType) was manipulated across three levels; NoSim, LoSim, and HiSim indicate the no similarity, low similarity, and high similarity conditions, respectively. PrimeRel indicates the relation that both Prime1 and Prime2 compounds instantiate (AN = Adj+N phrases, N = monosyllabic nouns); TargRel indicates the relation that a target compound instantiate. Again, we point out that regarding our research question, the relational similarity between prime and target compounds matters more than the specific classification of compounds into relation classes. The card sorting data clearly suggests that relational similarity was higher in the high similarity condition than in the low similarity condition.

SetID	TargType	Cond	Prime1	Prime2	Target	PrimeRel	TargRel
1	Opaque	NoSim	cheap jackets	cute shoes	sandcastles	AN	H-MADE-OF-M
1	Opaque	LoSim	stock yards	bachelor rooms	sandcastles	H-FOR-M	H-MADE-OF-M

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SetID	TargType	Cond	Prime1	Prime2	Target	PrimeRel	TargRel
1	Opaque	HiSim	glass doors	leather pants	sandcastles	H-MADE-OF-M	H-MADE-OF-M
2	Opaque	NoSim	cheap jackets	cute shoes	staircases	AN	H-CONTAIN-M
2	Opaque	LoSim	glass doors	leather pants	staircases	H-MADE-OF-M	H-CONTAIN-M
2	Opaque	HiSim	potion bottles	picture albums	staircases	H-CONTAIN-M	H-CONTAIN-M
3	Opaque	NoSim	cheap jackets	cute shoes	cupboards	AN	H-FOR-M
3	Opaque	LoSim	potion bottles	picture albums	cupboards	H-CONTAIN-M	H-FOR-M
3	Opaque	HiSim	stock yards	bachelor rooms	cupboards	H-FOR-M	H-FOR-M
4	Opaque	NoSim	unfair laws	illegal drugs	grasshoppers	AN	H-IN-M
4	Opaque	LoSim	juice stains	alumni money	grasshoppers	M-CAUSE-H	H-IN-M
4	Opaque	HiSim	surface tensions	office friendships	grasshoppers	H-IN-M	H-IN-M
5	Opaque	NoSim	unfair laws	illegal drugs	hailstorms	AN	H-CONTAIN-M
5	Opaque	LoSim	surface tensions	office friendships	hailstorms	H-IN-M	H-CONTAIN-M
5	Opaque	HiSim	walnut cakes	vitamin shampoos	hailstorms	H-CONTAIN-M	H-CONTAIN-M
6	Opaque	NoSim	unfair laws	illegal drugs	moonlight	AN	M-CAUSE-H
6	Opaque	LoSim	walnut cakes	vitamin shampoos	moonlight	H-CONTAIN-M	M-CAUSE-H
6	Opaque	HiSim	juice stains	alumni money	moonlight	M-CAUSE-H	M-CAUSE-H
7	Opaque	NoSim	dark clouds	emotional movies	bloodlines	AN	H-MADE-OF-M
7	Opaque	LoSim	fitness shoes	steak knives	bloodlines	H-FOR-M	H-MADE-OF-M
7	Opaque	HiSim	mosquito clouds	lace handkerchiefs	bloodlines	H-MADE-OF-M	H-MADE-OF-M
8	Opaque	NoSim	dark clouds	emotional movies	boardrooms	AN	H-HAVE-M
8	Opaque	LoSim	mosquito clouds	lace handkerchiefs	boardrooms	H-MADE-OF-M	H-HAVE-M
8	Opaque	HiSim	college towns	statue halls	boardrooms	H-HAVE-M	H-HAVE-M
9	Opaque	NoSim	dark clouds	emotional movies	hairbrushes	AN	H-FOR-M
9	Opaque	LoSim	college towns	statue halls	hairbrushes	H-HAVE-M	H-FOR-M
9	Opaque	HiSim	fitness shoes	steak knives	hairbrushes	H-FOR-M	H-FOR-M
10	Opaque	NoSim	terrible pains	shabby lodges	silkworms	AN	H-MAKE-M
10	Opaque	LoSim	beach balls	ground floors	silkworms	H-IN-M	H-MAKE-M
10	Opaque	HiSim	coke machines	widget factories	silkworms	H-MAKE-M	H-MAKE-M
11	Opaque	NoSim	terrible pains	shabby lodges	warships	AN	H-FOR-M
11	Opaque	LoSim	coke machines	widget factories	warships	H-MAKE-M	H-FOR-M
11	Opaque	HiSim	pet sprays	security lenses	warships	H-FOR-M	H-FOR-M
12	Opaque	NoSim	terrible pains	shabby lodges	backpacks	AN	H-IN-M
12	Opaque	LoSim	pet sprays	security lenses	backpacks	H-FOR-M	H-IN-M
12	Opaque	HiSim	beach balls	ground floors	backpacks	H-IN-M	H-IN-M
13	Opaque	NoSim	angry parents	bumpy trails	bathrobes	AN	H-FOR/DURING-M
13	Opaque	LoSim	cave prayers	space journeys	bathrobes	H-IN-M	H-FOR/DURING-M
13	Opaque	HiSim	rain shoes	tennis rackets	bathrobes	H-FOR/DURING-M	H-FOR/DURING-M
14	Opaque	NoSim	angry parents	bumpy trails	catfish	AN	H-BE-M
14	Opaque	LoSim	rain shoes	tennis rackets	catfish	H-FOR/DURING-M	H-BE-M
14	Opaque	HiSim	star shapes	box kites	catfish	H-BE-M	H-BE-M
15	Opaque	NoSim	angry parents	bumpy trails	stomachaches	AN	H-IN-M
15	Opaque	LoSim	star shapes	box kites	stomachaches	H-BE-M	H-IN-M
15	Opaque	HiSim	cave prayers	space journeys	stomachaches	H-IN-M	H-IN-M
16	Opaque	NoSim	clean rooms	plain pants	groundhogs	AN	H-IN-M
16	Opaque	LoSim	bicycle trails	baby chairs	groundhogs	H-FOR-M	H-IN-M
16	Opaque	HiSim	island birds	field mice	groundhogs	H-IN-M	H-IN-M
17	Opaque	NoSim	clean rooms	plain pants	meatballs	AN	H-MADE-OF-M
17	Opaque	LoSim	island birds	field mice	meatballs	H-IN-M	H-MADE-OF-M

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SetID	TargType	Cond	Prime1	Prime2	Target	PrimeRel	TargRel
17	Opaque	HiSim	copper coins	paper magazines	meatballs	H-MADE-OF-M	H-MADE-OF-M
18	Opaque	NoSim	clean rooms	plain pants	toothbrushes	AN	H-FOR-M
18	Opaque	LoSim	copper coins	paper magazines	toothbrushes	H-MADE-OF-M	H-FOR-M
18	Opaque	HiSim	bicycle trails	baby chairs	toothbrushes	H-FOR-M	H-FOR-M
19	Opaque	NoSim	dangerous pills	favorite lotions	earthworms	AN	H-IN-M
19	Opaque	LoSim	jewel stores	cranberry bowls	earthworms	H-CONTAIN-M	H-IN-M
19	Opaque	HiSim	desert lizards	water snakes	earthworms	H-IN-M	H-IN-M
20	Opaque	NoSim	dangerous pills	favorite lotions	campgrounds	AN	H-FOR-M
20	Opaque	LoSim	desert lizards	water snakes	campgrounds	H-IN-M	H-FOR-M
20	Opaque	HiSim	study lamps	hair lotions	campgrounds	H-FOR-M	H-FOR-M
21	Opaque	NoSim	dangerous pills	favorite lotions	toolboxes	AN	H-CONTAIN-M
21	Opaque	LoSim	study lamps	hair lotions	toolboxes	H-FOR-M	H-CONTAIN-M
21	Opaque	HiSim	jewel stores	cranberry bowls	toolboxes	H-CONTAIN-M	H-CONTAIN-M
22	Opaque	NoSim	expensive parties	boring life	ghostwriters	AN	H-BE-M
22	Opaque	LoSim	orange groves	flower gardens	ghostwriters	H-HAVE-M	H-BE-M
22	Opaque	HiSim	servant girls	citizen soldiers	ghostwriters	H-BE-M	H-BE-M
23	Opaque	NoSim	expensive parties	boring life	teapots	AN	H-FOR-M
23	Opaque	LoSim	servant girls	citizen soldiers	teapots	H-BE-M	H-FOR-M
23	Opaque	HiSim	graph paper	vacation houses	teapots	H-FOR-M	H-FOR-M
24	Opaque	NoSim	expensive parties	boring life	textbooks	AN	H-HAVE-M
24	Opaque	LoSim	graph paper	vacation houses	textbooks	H-FOR-M	H-HAVE-M
24	Opaque	HiSim	orange groves	flower gardens	textbooks	H-HAVE-M	H-HAVE-M
25	Opaque	NoSim	recent wars	priceless jewels	snowmen	AN	H-MADE-OF-M
25	Opaque	LoSim	coast guards	beach balls	snowmen	H-IN-M	H-MADE-OF-M
25	Opaque	HiSim	straw roofs	iron fences	snowmen	H-MADE-OF-M	H-MADE-OF-M
26	Opaque	NoSim	recent wars	priceless jewels	headmasters	AN	H-BE-M
26	Opaque	LoSim	straw roofs	iron fences	headmasters	H-MADE-OF-M	H-BE-M
26	Opaque	HiSim	child actors	woman doctors	headmasters	H-BE-M	H-BE-M
27	Opaque	NoSim	recent wars	priceless jewels	snowboards	AN	H-IN-M
27	Opaque	LoSim	child actors	woman doctors	snowboards	H-BE-M	H-IN-M
27	Opaque	HiSim	coast guards	beach balls	snowboards	H-IN-M	H-IN-M
28	Opaque	NoSim	dense forests	reckless clowns	bathtubs	AN	H-FOR-M
28	Opaque	LoSim	cigarette fires	bullet scars	bathtubs	M-CAUSES-H	H-FOR-M
28	Opaque	HiSim	cooking utensils	rescue equipments	bathtubs	H-FOR-M	H-FOR-M
29	Opaque	NoSim	dense forests	reckless clowns	gunboats	AN	H-HAVE-M
29	Opaque	LoSim	cooking utensils	rescue equipments	gunboats	H-FOR-M	H-HAVE-M
29	Opaque	HiSim	fruit baskets	dolphin aquariums	gunboats	H-HAVE-M	H-HAVE-M
30	Opaque	NoSim	dense forests	reckless clowns	handprints	AN	M-CAUSES-H
30	Opaque	LoSim	fruit baskets	dolphin aquariums	handprints	H-HAVE-M	M-CAUSES-H
30	Opaque	HiSim	cigarette fires	bullet scars	handprints	M-CAUSES-H	M-CAUSES-H
31	Opaque	NoSim	official actions	arduous journeys	bathrooms	AN	H-FOR-M
31	Opaque	LoSim	juice bowls	jewel boxes	bathrooms	H-CONTAIN-M	H-FOR-M
31	Opaque	HiSim	rest chairs	hunting lands	bathrooms	H-FOR-M	H-FOR-M
32	Opaque	NoSim	official actions	arduous journeys	roommates	AN	H-IN-M
32	Opaque	LoSim	rest chairs	hunting lands	roommates	H-FOR-M	H-IN-M
32	Opaque	HiSim	church fires	ocean clouds	roommates	H-IN-M	H-IN-M
33	Opaque	NoSim	official actions	arduous journeys	gearboxes	AN	H-CONTAIN-M
33	Opaque	LoSim	church fires	ocean clouds	gearboxes	H-IN-M	H-CONTAIN-M

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SetID	TargType	Cond	Prime1	Prime2	Target	PrimeRel	TargRel
33	Opaque	HiSim	juice bowls	jewel boxes	gearboxes	H-CONTAIN-M	H-CONTAIN-M
34	Opaque	NoSim	scary stories	warm houses	mailboxes	AN	H-FOR-M
34	Opaque	LoSim	protein drugs	nut breads	mailboxes	H-CONTAIN-M	H-FOR-M
34	Opaque	HiSim	sand equipments	baby fences	mailboxes	H-FOR-M	H-FOR-M
35	Opaque	NoSim	scary stories	warm houses	websites	AN	H-IN-M
35	Opaque	LoSim	sand equipments	baby chairs	websites	H-FOR-M	H-IN-M
35	Opaque	HiSim	ice holes	hand scars	websites	H-IN-M	H-IN-M
36	Opaque	NoSim	scary stories	warm houses	sandlots	AN	H-CONTAIN-M
36	Opaque	LoSim	ice holes	hand scars	sandlots	H-IN-M	H-CONTAIN-M
36	Opaque	HiSim	protein drugs	nut breads	sandlots	H-CONTAIN-M	H-CONTAIN-M
1	Transparent	NoSim	rickshaws	scallops	leather pants	N	H-MADE-OF-M
1	Transparent	LoSim	birdhouses	cupboards	leather pants	H-FOR-M	H-MADE-OF-M
1	Transparent	HiSim	snowballs	sandcastles	leather pants	H-MADE-OF-M	H-MADE-OF-M
2	Transparent	NoSim	rickshaws	scallops	potion bottles	N	H-CONTAIN-M
2	Transparent	LoSim	snowballs	sandcastles	potion bottles	H-MADE-OF-M	H-CONTAIN-M
2	Transparent	HiSim	matchboxes	staircases	potion bottles	H-CONTAIN-M	H-CONTAIN-M
3	Transparent	NoSim	rickshaws	scallops	bachelor rooms	N	H-FOR-M
3	Transparent	LoSim	matchboxes	staircases	bachelor rooms	H-CONTAIN-M	H-FOR-M
3	Transparent	HiSim	birdhouses	cupboards	bachelor rooms	H-FOR-M	H-FOR-M
4	Transparent	NoSim	gazelles	carousels	office friendships	N	H-IN-M
4	Transparent	LoSim	torchlight	moonlight	office friendships	M-CAUSE-H	H-IN-M
4	Transparent	HiSim	sandworms	grasshoppers	office friendships	H-IN-M	H-IN-M
5	Transparent	NoSim	gazelles	carousels	vitamin shampoos	N	H-CONTAIN-M
5	Transparent	LoSim	sandworms	grasshoppers	vitamin shampoos	H-IN-M	H-CONTAIN-M
5	Transparent	HiSim	woodlands	hailstorms	vitamin shampoos	H-CONTAIN-M	H-CONTAIN-M
6	Transparent	NoSim	gazelles	carousels	alumni money	N	M-CAUSE-H
6	Transparent	LoSim	woodlands	hailstorms	alumni money	H-CONTAIN-M	M-CAUSE-H
6	Transparent	HiSim	torchlight	moonlight	alumni money	M-CAUSE-H	M-CAUSE-H
7	Transparent	NoSim	sophomores	trombones	lace handkerchiefs	N	H-MADE-OF-M
7	Transparent	LoSim	shoestrings	hairbrushes	lace handkerchiefs	H-FOR-M	H-MADE-OF-M
7	Transparent	HiSim	woodpiles	bloodlines	lace handkerchiefs	H-MADE-OF-M	H-MADE-OF-M
8	Transparent	NoSim	sophomores	trombones	statue halls	N	H-HAVE-M
8	Transparent	LoSim	woodpiles	bloodlines	statue halls	H-MADE-OF-M	H-HAVE-M
8	Transparent	HiSim	junkyards	boardrooms	statue halls	H-HAVE-M	H-HAVE-M
9	Transparent	NoSim	sophomores	trombones	steak knives	N	H-FOR-M
9	Transparent	LoSim	junkyards	boardrooms	steak knives	H-HAVE-M	H-FOR-M
9	Transparent	HiSim	shoestrings	hairbrushes	steak knives	H-FOR-M	H-FOR-M
10	Transparent	NoSim	mannequins	tortoises	coke machines	N	H-MAKE-M
10	Transparent	LoSim	roadhouses	backpacks	coke machines	H-IN-M	H-MAKE-M
10	Transparent	HiSim	bathhouses	silkworms	coke machines	H-MAKE-M	H-MAKE-M
11	Transparent	NoSim	mannequins	tortoises	security lenses	N	H-FOR-M
11	Transparent	LoSim	bathhouses	silkworms	security lenses	H-MAKE-M	H-FOR-M
11	Transparent	HiSim	skateboards	warships	security lenses	H-FOR-M	H-FOR-M
12	Transparent	NoSim	mannequins	tortoises	ground floors	N	H-IN-M
12	Transparent	LoSim	skateboards	warships	ground floors	H-FOR-M	H-IN-M
12	Transparent	HiSim	roadhouses	backpacks	ground floors	H-IN-M	H-IN-M
13	Transparent	NoSim	syringes	satchels	rain shoes	N	H-FOR/DURING-M
13	Transparent	LoSim	seaweeds	stomachaches	rain shoes	H-IN-M	H-FOR/DURING-M

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SetID	TargType	Cond	Prime1	Prime2	Target	PrimeRel	TargRel
13	Transparent	HiSim	battleships	bathrobes	rain shoes	H-FOR/DURING-M	H-FOR/DURING-M
14	Transparent	NoSim	syringes	satchels	box kites	N	H-BE-M
14	Transparent	LoSim	battleships	bathrobes	box kites	H-FOR/DURING-M	H-BE-M
14	Transparent	HiSim	tapeworms	catfish	box kites	H-BE-M	H-BE-M
15	Transparent	NoSim	syringes	satchels	cave prayers	N	H-IN-M
15	Transparent	LoSim	tapeworms	catfish	cave prayers	H-BE-M	H-IN-M
15	Transparent	HiSim	seaweeds	stomachaches	cave prayers	H-IN-M	H-IN-M
16	Transparent	NoSim	consoles	hatchets	island birds	N	H-IN-M
16	Transparent	LoSim	armholes	toothbrushes	island birds	H-FOR-M	H-IN-M
16	Transparent	HiSim	seahorses	groundhogs	island birds	H-IN-M	H-IN-M
17	Transparent	NoSim	consoles	hatchets	paper magazines	N	H-MADE-OF-M
17	Transparent	LoSim	seahorses	groundhogs	paper magazines	H-IN-M	H-MADE-OF-M
17	Transparent	HiSim	cheesecakes	meatballs	paper magazines	H-MADE-OF-M	H-MADE-OF-M
18	Transparent	NoSim	consoles	hatchets	baby chairs	N	H-FOR-M
18	Transparent	LoSim	cheesecakes	meatballs	baby chairs	H-MADE-OF-M	H-FOR-M
18	Transparent	HiSim	armholes	toothbrushes	baby chairs	H-FOR-M	H-FOR-M
19	Transparent	NoSim	anthems	scoundrels	water snakes	N	H-IN-M
19	Transparent	LoSim	coatrooms	toolboxes	water snakes	H-CONTAIN-M	H-IN-M
19	Transparent	HiSim	backyards	earthworms	water snakes	H-IN-M	H-IN-M
20	Transparent	NoSim	anthems	scoundrels	study lamps	N	H-FOR-M
20	Transparent	LoSim	backyards	earthworms	study lamps	H-IN-M	H-FOR-M
20	Transparent	HiSim	notepapers	campgrounds	study lamps	H-FOR-M	H-FOR-M
21	Transparent	NoSim	anthems	scoundrels	cranberry bowls	N	H-CONTAIN-M
21	Transparent	LoSim	notepapers	campgrounds	cranberry bowls	H-FOR-M	H-CONTAIN-M
21	Transparent	HiSim	coatrooms	toolboxes	cranberry bowls	H-CONTAIN-M	H-CONTAIN-M
22	Transparent	NoSim	cheetahs	throttles	citizen soldiers	N	H-BE-M
22	Transparent	LoSim	graph papers	textbooks	citizen soldiers	H-HAVE-M	H-BE-M
22	Transparent	HiSim	girlfriends	ghostwriters	citizen soldiers	H-BE-M	H-BE-M
23	Transparent	NoSim	cheetahs	throttles	vacation houses	N	H-FOR-M
23	Transparent	LoSim	girlfriends	ghostwriters	vacation houses	H-BE-M	H-FOR-M
23	Transparent	HiSim	fireplaces	teapots	vacation houses	H-FOR-M	H-FOR-M
24	Transparent	NoSim	cheetahs	throttles	flower gardens	N	H-HAVE-M
24	Transparent	LoSim	fireplaces	teapots	flower gardens	H-FOR-M	H-HAVE-M
24	Transparent	HiSim	graveyards	textbooks	flower gardens	H-HAVE-M	H-HAVE-M
25	Transparent	NoSim	raccoons	poodles	straw roofs	N	H-MADE-OF-M
25	Transparent	LoSim	headphones	snowboards	straw roofs	H-IN-M	H-MADE-OF-M
25	Transparent	HiSim	cardboards	snowmen	straw roofs	H-MADE-OF-M	H-MADE-OF-M
26	Transparent	NoSim	raccoons	poodles	woman doctors	N	H-BE-M
26	Transparent	LoSim	cardboards	snowmen	woman doctors	H-MADE-OF-M	H-BE-M
26	Transparent	HiSim	boyfriends	headmasters	woman doctors	H-BE-M	H-BE-M
27	Transparent	NoSim	raccoons	poodles	beach balls	N	H-IN-M
27	Transparent	LoSim	boyfriends	headmasters	beach balls	H-BE-M	H-IN-M
27	Transparent	HiSim	headphones	snowboards	beach balls	H-IN-M	H-IN-M
28	Transparent	NoSim	guillotines	thermostats	cooking utensils	N	H-FOR-M
28	Transparent	LoSim	fleabites	handprints	cooking utensils	M-CAUSES-H	H-FOR-M
28	Transparent	HiSim	paintbrushes	bathtubs	cooking utensils	H-FOR-M	H-FOR-M
29	Transparent	NoSim	guillotines	thermostats	dolphin aquariums	N	H-HAVE-M
29	Transparent	LoSim	paintbrushes	bathtubs	dolphin aquariums	H-FOR-M	H-HAVE-M

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SetID	TargType	Cond	Prime1	Prime2	Target	PrimeRel	TargRel
29	Transparent	HiSim	newspapers	gunboats	dolphin aquariums	H-HAVE-M	H-HAVE-M
30	Transparent	NoSim	guillotines	thermostats	bullet scars	N	M-CAUSES-H
30	Transparent	LoSim	newspapers	gunboats	bullet scars	H-HAVE-M	M-CAUSES-H
30	Transparent	HiSim	fleabites	handprints	bullet scars	M-CAUSES-H	M-CAUSES-H
31	Transparent	NoSim	scaffolds	bailiffs	hunting lands	N	H-FOR-M
31	Transparent	LoSim	bedrooms	gearboxes	hunting lands	H-CONTAIN-M	H-FOR-M
31	Transparent	HiSim	breadboards	bathrooms	hunting lands	H-FOR-M	H-FOR-M
32	Transparent	NoSim	scaffolds	bailiffs	ocean clouds	N	H-IN-M
32	Transparent	LoSim	breadboards	bathrooms	ocean clouds	H-FOR-M	H-IN-M
32	Transparent	HiSim	streetlights	roommates	ocean clouds	H-IN-M	H-IN-M
33	Transparent	NoSim	scaffolds	bailiffs	jewel boxes	N	H-CONTAIN-M
33	Transparent	LoSim	streetlights	roommates	jewel boxes	H-IN-M	H-CONTAIN-M
33	Transparent	HiSim	bedrooms	gearboxes	jewel boxes	H-CONTAIN-M	H-CONTAIN-M
34	Transparent	NoSim	albatrosses	porcupines	baby fences	N	H-FOR-M
34	Transparent	LoSim	sandstorms	sandlots	baby fences	H-CONTAIN-M	H-FOR-M
34	Transparent	HiSim	bookcases	mailboxes	baby fences	H-FOR-M	H-FOR-M
35	Transparent	NoSim	albatrosses	porcupines	hand scars	N	H-IN-M
35	Transparent	LoSim	bookcases	mailboxes	hand scars	H-FOR-M	H-IN-M
35	Transparent	HiSim	altarpieces	websites	hand scars	H-IN-M	H-IN-M
36	Transparent	NoSim	albatrosses	porcupines	nut breads	N	H-CONTAIN-M
36	Transparent	LoSim	altarpieces	websites	nut breads	H-IN-M	H-CONTAIN-M
36	Transparent	HiSim	sandstorms	sandlots	nut breads	H-CONTAIN-M	H-CONTAIN-M

Appendix D

Materials used in a free card sorting task

A set of 630—384 transparent and 246 opaque—compounds was used in the card sorting task (see Chapter 3).

Transparent compounds are as follows: bacon grease, court decision, yacht club, ghetto turmoil, money prayers, glass eye, ice hole, street riot, coat store, cancer gene, company equipment, winter season, suspense film, hill trails, fish scale, rest chair, voice commercial, fish farm, building roof, citizen soldier, finger cymbals, freedom war, castle hall, wind farm, surprise attack, plum wine, office friendship, flower garden, future shock, olive oil, superhero movie, rice paper, rescue equipment, wilderness road, wrinkle lotion, stock market, salt lake, winter storm, heat pants, boat adventure, cold crack, cooking utensil, company asset, music box, juice bowl, investment benefit, time card, soldier ant, people power, river sports, snow blindness, hydrogen bomb, water bird, prairie adventure, leather album, kid book, hand brake, cane sugar, satellite nation, March sales, island bird, moisture shampoo, weekend boredom, peanut butter, red-card foul, allergy pill, basketball season, safety wall, potion bottle, summer travel, picture album, tree trunk, cocaine death, evening jour-

ney, water pants, risk behavior, plasma cloud, leather pants, college town, laugh wrinkle, enemy strength, sand dune, fertility pill, road trip, worker team, vacation house, security lens, history conference, lightning rod, warrior caste, infection germ, copper bottle, beach party, baby chair, explosion turmoil, tennis racket, ion cloud, kennel puppy, ball sports, candy cigarette, chat room, tobacco ash, morning cloud, seaside bungalow, wool jacket, birth pain, stone wall, travel album, table bowl, vegetable soup, island life, tree farm, sea battle, coast guard, grain alcohol, nut bread, sports magazine, rubber shoes, tear gas, separation anxiety, government forest, union lawyer, stamina food, paper money, metal money, corn chip, landfill bird, daisy chain, stamina soup, malaria mosquito, pumpkin pie, bronze statue, chimney roof, rain shoes, nose drop, cancer drug, summer months, accident weather, sunset prayer, ground floor, dandruff shampoo, lifetime achievement, brain disease, mountain lion, accident carelessness, sugar cube, entrance hall, child actor, sound card, pine tree, physics homework, copyright law, basket store, sister node, cranberry bowl, school achievement, paper magazine, vacuum cleaner, hair lotion, glass door, summer sports, mud boots, health club, servant girl, classroom tension, aerosol spray, library book, starvation diet, song commercial, health diet, hunting land, rubber headache, bug spray, boom box, star shape, disease germ, ice storm, woman doctor, university grove, protein drug, trash fish, budget speech, coal dust, dolphin aquarium, spleen disease, autumn rain, party member, field mouse, book club, surface tension, swamp forest, alligator leather, dust goggle, wedding cake, attic floor, morphology lecture, color television, song bird, coal stove, morning commercial, moth hole, math magazine, bond paper, student magazine, vapor lock, fitness shoes, testtube baby, fertility disease, juice stains, cigarette fire, steak knife, rye whiskey, air pressure, home remedy, city wall, spring party, Iraq war, stock yard, coffee nerve, foam factory, automobile plant, suicide bombing, space journey, government employment, weekday life, trauma event, pocket money, pupil achievement, steel helmet, walnut cake, flu virus,

wind jacket, sun umbrella, pet family, flash card, sand equipment, pest poisons, call box, cream sauce, torture law, reindeer land, baby fences, drug death, cucumber disease, radio communication, sob story, finance law, ocean cloud, copper coin, study lamp, tractor engine, bullet scar, citrus lotion, voice vote, store clothes, college adventure, shirt collar, jewel box, dust storm, summer safari, pet spray, queen bee, job tension, mosquito cloud, chair doctor, Thanksgiving guest, country factory, lace handkerchief, church fire, fruit basket, apple cake, air ball, baby doctor, burglar fence, deficiency disease, fatigue headache, winter bird, box kite, heart drug, enforcement action, wolf story, adventure story, student committee, party life, night battle, mountain range, spa resort, air brake, alumni money, growth hormone, death battle, anxiety situation, tax law, sea breeze, disaster flick, company store, insect homework, water wheel, peephole door, highland forest, book party, cave prayer, picture book, abortion vote, bachelor room, desert lizard, horse doctor, pole height, lemon peel, chocolate bar, wind burn, graph paper, abortion problem, onion tear, hand scar, heat rash, midnight train, noise walls, beach ball, orange grove, lifetime lawyer, tire rim, melon peel, sweat jacket, courtroom action, adolescence turmoil, weekend lodge, machine translation, smoke signal, kitchen door, family antique, steam iron, love song, iron fence, dog virus, county land, outside situation, investment decision, oil money, coke machine, peer therapy, evening hours, oak lodge, measles vaccine, water snake, pressure cooker, pool house, statue hall, evening grove, straw roof, energy emergency, apple cores, midnight headache, horror movie, sports activities, autumn trail, school album, water mark, pope lawyer, herb pills, extension ladder, bicycle trails, sap tree, family problem, widget factory, fruit tree, mountain magazine, cough medicine, time trial, ferry journey, hotel room, war club, ankle pain, gas stove, ball boy, mountain lodge, laugh hiccup, vitamin shampoo, airport store, childhood dream, April homework, jewel store, coffee break, stage fright.

Opaque compounds are as follows: pancake, bathroom, airline, ballroom, cupboard,

choirboy, waveform, basketball, staircase, grasshopper, hailstorm, hookworm, airplay, moonlight, footstep, bloodline, campground, junkyard, hairbrush, boardroom, sunburst, earache, gearbox, bookshelf, barnyard, homesite, nightclub, jawbone, lighthouse, mothball, tombstone, birthday, penlight, catfish, goldfish, sandlot, bathrobe, sailboat, headlight, fingerprint, courtyard, centerpiece, backpack, goldbug, warship, silkworm, lifestyle, airstrip, paintbrush, ringworm, mailbox, birdhouse, skateboard, honeycomb, ghostwriter, housecoat, teapot, spotlight, woodland, hallway, sunlight, baseline, headmaster, axman, newsboy, teacup, toothbrush, artwork, snowboard, stoplight, firestone, nightspot, backboard, sidearm, roadhouse, textbook, batboy, sandbag, seashore, budworm, bathtub, cowfish, postman, heartworm, armhole, fireworks, groundnut, gunboat, needlework, gemstone, airport, altarpiece, fireboat, beeline, woodworm, housewife, earplug, milestone, spaceflight, beachwear, breadboard, rainbow, icebox, starfish, sandstorm, seafood, birthstone, woodshed, bookplate, bathhouse, clockwork, handprint, website, deeryard, churchyard, seaweed, sunfish, birthplace, lakeshore, airhole, meatball, snowball, wheelchair, braincase, sandcastle, bookcase, headache, coatroom, daylight, sawfish, rattlesnake, necktie, floodlight, windmill, railway, bellboy, cheesesteak, bedbug, spaceship, woodpile, newspaper, earphone, backbone, landlady, firearm, steamboat, groundhog, bookend, farmyard, penknife, brickyard, airway, snowstorm, shoestring, folklore, barroom, doormat, banknote, roommate, railroad, sandworm, swordfish, bedroom, sandpaper, thunderstorm, schoolmate, gaslight, archway, classroom, seahorse, lifeguard, cowboy, boyfriend, sunshine, football, birdseed, boxboard, masterpiece, blockhouse, earlobe, cheesecake, daydream, armchair, houseboat, backyard, matchbox, horseman, backlight, fleabite, sidestep, doorstep, gravestone, classmate, notepaper, wardrobe, landlord, footstone, bottleneck, brainstorm, broomstick, backache, honeybee, streetlight, firestorm, candlestick, airspace, cloakroom, tapeworm, stomachache, toolbox, earring, headphone, billboard, flypaper, graveyard, airship, girlfriend,

doorbell, cardboard, timetable, shoelace, fireplace, torchlight, doorway, catfight, campfire, weekend, firefly, wallpaper, housemate, whaleboat, footprint, snowman, battleship, belly-ache, baseball, eyeball, fireplug, background, earthworm, stoneboat, rainstorm, airspeed, matchstick, starlight, airfare.

Appendix E

The instruction used in a free card sorting task

Noun-noun compounds can be understood by finding a (semantic or thematic) relation that connect component nouns. For example, a *mountain magazine* means a magazine that *is about* mountains. A *mountain hut* might mean a hut that *is located in* a mountain. An *oak hut* would mean a hut that *is made of* oak (trees). Note that the same word can be used in many different relations. Various semantic relations can be found in English compound nouns but it is often difficult to verbalize the relations.

In this task, you will be given 632 cards each of which contains one noun-noun compound and asked to sort them into ANY number of groups (at least more than one group) such that each group contains similar noun-noun compounds in terms of the relations that they use. In other words, you are asked to sort noun-noun compounds based on relational similarity. In this task, for example, you might want to group “mountain hut” together with “desert rat” which means a rat that lives in a desert. It is also possible for you to keep them separate from each other if you think they use different relations. There is no clear rule so

please follow your intuition. But it is highly unlikely that you want to group “mountain hut” together with “oak hut,” although both are a type of huts so they (the objects [or concepts] referred to by the expressions) look similar in a sense. You will do this task based on relational similarity.

The task has two stages. Below is presented a specific instruction. Please read it carefully and follow it when you are doing this task. A caveat: While you are at Stage 1, do not think about Stage 2. If you have any question, please feel free to ask me at any time.

Stage 1.

1. Shuffle 632 cards randomly.
2. Pick up a card from the top and think about the meaning of a compound written on the card. Then, consider what relation is used to connect two component nouns to form the compound meaning. Typically it is quite difficult to verbalize the relation so do not try to do that.
3. If you think the current noun-noun compound can be grouped together with a group of cards (if you have already formed at least one group of cards) in terms of the relations, place the current card on the top of the card pile. If you think the current noun-noun compound cannot go with any of groups that you have formed, place the current card separate from other groups to make a new group. Thus, you need to focus on RELATIONAL SIMILARITY. Instead of verbalizing the relation used in each compound and checking if the relations are same, try to look at the noun-noun compounds (the current noun-noun compound and other noun-noun compound from the candidate group) side by side and judge if they use similar relations. Please reserve a group where you can place the noun-noun compounds that you don't understand. This group will be labeled ETC later.

4. Go to 2 and repeat the procedure. During the task at this stage, you can freely reorganize (regroup) the sorted cards.

When you finish the task, you will have N groups of cards ($N > 1$) and one ETC group. Place a card guide on the top of each card pile and put a label on its tab. For example, if you have 10 groups, you can label the groups as A, B, C, ..., J. If you have more than 26 groups, then, you can use A, B, ..., Z, AA, AB, ..., etc.

Stage 2.

For each group of cards, repeat the same procedure. In other words, please sort the cards from the same group into multiple subgroups based on relational similarity as you did at the first stage. For example, let us suppose that you sorted the card pile (labeled as B) into three subgroups. Then, place a card guide on the top of each subgroup (you can use the card guide (labeled B) for one of the new subgroups). Then, label them like B1, B2, B3. Note that each group can have different numbers of subgroups. Sometimes you might not want to sort a card pile into multiple subgroups because you think the noun-noun compounds in the group use very similar relations. In this case, you don't need to sort them into subgroups and you can keep the original sorting.

At the end of task, for example, you might have 18 groups (the number is very arbitrary and not related to any ideal number of groups) labeled A, B1, B2, B3, C, D, E1, E2, F1, F2, G, H1, H2, H3, H4, I, J1, J2 as well as a nonsense group labeled ETC. Of course, every single participant will have different groups.

Let us repeat again: Do not think about Stage 2 before you finish Stage 1. We want to collect some information about your "default" grouping of compounds.

Appendix F

The instruction used in a pairwise relational similarity rating task

Welcome!

In this experiment, you will be asked to rate the relational similarity of multiple pairs of noun-noun combinations. Relational similarity is defined as follows:

“Relational similarity refers to how similar the inferred relations are between two combinations of noun. For instance, because SOAP BASKET and CUCUMBER SALAD both have a CONTAINS relation, you might give them a high rating. Note that this is different from the more common form of similarity in which two concepts have the same features or belong to the same category. So although cucumbers and pickles are pretty similar, the relation for CUCUMBER SALAD may not be very similar to the relation for PICKLE JUICE, and therefore you might give them a lower rating.” (Estes & Jones, 2006)

Here are some practice trials. Please rate the relational similarity by circling a number.

clay potteries ----- aluminum cages

1 ----- 2 ----- 3 ----- 4 ----- 5 ----- 6 ----- 7

not at all relationally similar

very relationally similar

charcoal pencils ----- beef broth

1 ----- 2 ----- 3 ----- 4 ----- 5 ----- 6 ----- 7

not at all relationally similar

very relationally similar

pumpkin pies ----- feather pillows

1 ----- 2 ----- 3 ----- 4 ----- 5 ----- 6 ----- 7

not at all relationally similar

very relationally similar

water birds ----- baby chairs

1 ----- 2 ----- 3 ----- 4 ----- 5 ----- 6 ----- 7

not at all relationally similar

very relationally similar

If you have any questions, please ask them now.

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